Forecasting Travel Demand on Idaho Highways

Summary of Time-Series Analysis Methodology

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1. INTRODUCTION

In October 1990, the Idaho Transportation Department and the University of Idaho initiated a research project to develop a methodology to forecast future traffic demand on Idaho highways. The objective of this project is to:

> develop a traffic forecasting model to forecast total traffic, commercial traffic, and truck weight or EASLS. These forecasts will be used by ITD traffic, materials, and pavements engineers, highway designers, and planners in evaluating various projects and improvements.

The original scope of work included the following tasks:

1. Conduct review of current methodologies and procedures used by other state transportation departments.

2. Review other relevant literature and research.

3. Assemble data base of historical ITD data including traffic, economic, and other relevant data.

4. Develop context for requirements/usage for forecasting models.

5. Statistical analysis of factors that affect traffic volumes at state, regional, and local level.

6. Test and proof of the models.

7. Prepare models and methodology.

8. Prepare final report.

A review of the literature showed that two broad set of techniques have been developed over the years by traffic analysts. The first relies on an extensive set of transportation and socio-economic data to develop travel forecasts on a spatial or zonal level. This technique, sometimes known as the four-step process (for the four steps involved, trip generation, trip distribution, modal split, and traffic assignment), is commonly used in urban areas with extensive travel and socio-economic data bases. The second technique, broadly known as time series analysis, is based on understanding the changes in travel demand over time, and the factors or processes that govern these changes. This technique requires a data base with travel demand information kept at regular time intervals, usually monthly or yearly intervals.

Time-series analysis was selected for use in this study for several reasons. The Idaho Transportation Department maintains an array of Automated Traffic Recorders, or ATR's, throughout the state that have been counting and recording average daily traffic flow rates since the 1970's. Some stations now have records exceeding 240 consecutive months of average daily traffic flows over a twenty year period. In addition, ITD does not maintain, except in a selected few areas, the data on travel patterns and socio-economic characteristics required for the four-step travel demand forecasting models.

Time-series analysis is actually a broad range of analysis techniques that include regression analysis and ARIMA (or Box-Jenkins) analysis. All of these techniques use average daily traffic (or a related variable) as the dependent variable. In addition, some use independent variables that attempt to explain the variation in traffic demand over time, while others use the trends or statistical correlation information contained in the traffic demand information to forecast future traffic volumes. For statistical reasons, however, it is important to carefully consider the error terms that are included as part of any forecasting model using time series data.

Two time series models were selected as the basis for the major focus of this study, the univariate model and the multivariate transfer function model. Both are based on the Box-Jenkins model and are members of the Autoregressive Integrated Moving Average (or ARIMA) family of time-series models. While this family of models has a long and complicated sounding name, and requires some degree of mastery that might seem intimidating at first, the models allow for a very flexible and powerful way of studying the nature of traffic demand variation over time.

The univariate ARIMA model can be written in the following form: the average daily traffic volume, or ADT, for a given month is a linear function of the volume measured in past months plus an error term.

$$ADT_t = \sum_i a_i \, ADT_{t-i} + e_t \tag{1}$$

The multivariate or transfer function ARIMA model considers both the past variation in the traffic volumes themselves as well as past variation in the variables that might explain this variation. One such model formulation is: the ADT for a given month is a function of past changes in explanatory variables X_i such as market size, travel costs, and system accessibility, as well as past variation in the traffic volumes (ADT) themselves.

$$ADT_t = \sum_i a_t \, ADT_{t-i} + \sum_i b_t \, X_{t-i} + e_t \qquad (2)$$

One of the advantages of this formulation is that lagged response can be directly accounted for. For example, an increase in the size of the travel market, as measured by the total number of workers employed during a given month, might not be evident for several months while the change in the cost of travel as measured by gasoline price might have a much more timely effect on traffic demand.

This report describes the results of this research project and the development of a traffic demand forecasting technique for forecasting future traffic volumes on Idaho highways.

- Chapter 2 includes a review of the literature and a summary of techniques developed by others, including a very important and relevant study by the Washington Department of Transportation.
- Chapters 3 and 4 include a detailed review of the data base that was compiled for this project. Chapter 3 includes monthly total ADT volumes taken from the ATR's located throughout the state's highway system. A total of 77 ATR stations have count histories of a least 180 consecutive months. Fifteen ATR stations have count histories of at least 48 consecutive months for total truck traffic. Chapter 4 includes a summary of the data base that was used to explain changes in traffic volumes. The variables include vehicle registration by county, employment by county, and gasoline price.
- Chapters 6 and 7 describe the results of the univariate and multivariate forecasting models for total traffic and for truck traffic.
- Chapter 8 presents a summary of the work accomplished during this study and the major conclusions that were developed.
- Chapter 9 lists the references that were consulted during this study.
- Several appendices are included the present details of the data base compiled.
    - Appendix A, Automatic Traffic Recorder Station Data
    - Appendix B, Traffic Volume Growth Trends
    - Appendix C, Traffic Volume Truck History Plots
    - Appendix D, Truck Volume Time History Plots
    - Appendix E, Time History Plots For Other Data
    - Appendix F, Time Series Analysis Model Development Methodology

CHAPTER 2. SUMMARY OF TRAFFIC DEMAND FORECASTING MODELS

2.1 Overview

A number of sources were consulted to identify previous work that has been completed relevant to the topic of this study. Section 2.2 describes a traffic forecasting guide developed for the Washington Department of Transportation. Because of it relevance to this current study, extensive excerpts from this guide are presented here. Section 2.3 discusses a new report from AASHTO that describes the importance of data quality and truth in data when preparing forecasts. Section 2.4 describes a set of models developed by Purdue University for the Indiana Department of Transportation to forecast traffic volumes on rural state highways based on past traffic trends and the variables that affect these trends. Section 2.5 describes travel demand forecasting studies that have used time series analysis techniques. Section 2.6 cites several other studies in which travel demand forecasting procedures are described.

2.2 Washington Department of Transportation Traffic Forecasting Guide

One of the more important studies identified during the literature search phase of this project was completed by Mark Hallenbeck of the Washington State Department of Transportation [x]. Hallenbeck's study, the WSDOT Traffic Forecasting Guide, is a broadly-based assessment of and guidelines for using travel demand techniques that can be used by transportation engineers and planners in preparing forecasts for different kinds of transportation projects. Because of its importance, several key sections are summarized here. The guide includes six chapters: (1) introduction, (2) factors to consider when performing forecasts, (3) beginning the forecasting process, (4) selecting forecasting techniques, (5) performing the forecast, (6) review and presentation of the forecast.

Hallenbeck notes the purpose of the guide as follows. "The Washington State Department of Transportation has produced this guide to facilitate and improve the development of traffic forecasts that Department engineers or planners use. The guide is intended to help standardize the methodology for developing forecasts, assist in providing an *audit trail* of steps and assumptions behind the development of each forecast, and help ensure that the assumptions underlying the forecasting process are considered and carefully reviewed."

An overall context for forecasting is provided in the first chapter. "By nature, forecasting is an inexact science. The results are never *correct*, although a good forecast can be considered *accurate*. Historically, forecast work has been given much less attention that most other aspects of the design process. Consequently, forecasting has sometimes been done haphazardly, resulting in forecasts that have borne little resemblance to the traffic levels that have actually occurred over time. Persons untrained in forecasting and unaware of the impacts of poor traffic estimates on pavement and geometric design have used too little information and paid too little attention to basic assumptions (such as the expected growth of truck traffic) which have a significant impact on highway design, construction, and performance."

Chapter 2 of the report describes the factors to be considered when making forecasts. Four passages are excerpted here:

- "Transportation is not an end product. It is simply a means for accomplishing some other end. It is necessary only to allow some action to take place, whether that action is to move goods from where they are produced to where they are consumed, or to move a family from its house to the camping spot where it will vacation. Thus, traffic levels are not independent values, but are dependent on the level of activity that produces the demand for travel. (p 14)
- "However, because travel is important to so many activities, traffic levels are not a simple reflection of a small number of independent factors (e.g. population). The demand for travel is a complex function of a large number of factors relating to the general economic activity of a large geographic area, and the total number of people available to perform that travel. In simpler terms, traffic levels are a function of the number of people who want to travel, the cost of travel, the ease with which those persons can travel, and the availability of roads on which they can travel.
- "While this combination of factors is complex, we have an advantage when we perform traffic forecasts, in that we can measure the demand for traffic under present conditions. Then we must only forecast how traffic levels might change over time, given expected changes in population and economic activity. Thus, the forecaster must understand the level of traffic demand that currently exists on a project facility and then determine how that level of demand may change, given a set of expected economic and population forecasts.
- "These changes in population and economic activity will have a variety of impacts on existing travel demand. Some of these changes will take place quickly (a new factory opens, traffic levels increase immediately on the road that leads to it); some will take place slowly (as the population in an urban area increases over time, traffic levels increase as those new residents make trips); and other factors will have an impact somewhere in between.
- "In most cases a traffic forecast, and the load estimates that result from that forecast, consists of estimating three separate but related quantities for each of the roads (or road sections) within the project boundaries for each of the design years. These forecast quantities are (1) traffic volumes, (2) traffic composition (vehicle classification), and (3) vehicle weights or pavement damage factors, expressed as equivalent standard axle loads, or ESALs. (p 15)

The guide notes that each of these forecast quantities require different kinds of data. *Traffic volume forecasts* require the consideration of (1) impacts of localized population and employment changes, (2) impacts of external population and employment changes, (3) alternative routes, and (4) external factors. A *vehicle classification forecast* requires the consideration of (1) impacts of local economic activity, (2) alternative routes, (3) external factors, through traffic and statewide trends, (4) seasonal changes, and (5) time of day changes. *Truck weight forecasts* require the consideration of the kinds of trucks that will be using the facility.

Chapter 3 "...describes the initial steps in the forecasting process. ... These steps include the following: (1) becoming familiar with the project area, (2) understanding the scope, level of effort and time frame of the project, and (3) determining the end results that are required from a specific forecast."

Chapter 4 "...describes the steps that you should follow to select the appropriate tools for developing estimates that meet the needs determined in chapter 3. .. This guide describes a four phase process: (1) identify and request the data available for the forecast, (2) make a preliminary selection of the forecasting technique to be used, (3) collect and review the input information, and (4) revise the selection of forecasting technique(s) as necessary." A list of several of the common forecasting tools are summarized in this chapter. Most are data and computer modeling intensive.

Chapter 5 describes "... the specific steps that you must follow to perform a traffic forecast." The analysis techniques that are included in this chapter are: (1) trend analysis, (2) rural growth analysis, (3) and four-step modeling. *Trend analysis and rural growth analysis* are both done manually or with appropriate supporting software. "Trend analysis is the use of historical traffic count information to predict future traffic volumes. It can be used when several traffic counts near or within a project are available over time at the same location. Rural growth analysis relies on default growth rates, plus site specific information. It is to be used when insufficient data are available to perform either the trend analysis process or the four step modeling sequence. *The four step modeling process* ... is the most complex of the forecasting techniques and will be used the least often.

The first technique, *trend analysis*, is the process "... most appropriate for rural highways and older urban areas that are not expected to experience large amounts of traffic or economic growth during the design period. In addition, this procedure is to be followed only when a large number (five years or more) of traffic counts are available as a basis for a trend line. The trend line is estimated with a linear regression technique and the corresponding growth rate is then applied to the base year traffic estimate. Any necessary adjustments are then added to this growth estimate to account for specific growth areas (new factories, sub-divisions, etc) in or near the project. The vehicle mix is then adjusted to account for predicted changes in the state or local truck mix. Finally, the required design information (K, D, T) are updated to reflect the predicted traffic volumes." Several worksheets are included to assist the planner or engineer in preparing the forecasts. The specific steps to be followed in this forecasting process are listed in Table 1.

Table 1. Trend Analysis

■indicate the year for which the baseline traffic estimate is made
■list the initial traffic conditions
■indicate the length of the design period and forecast year
■calculate the historic growth patterns
■determine any mitigating circumstances
■forecast the traffic levels
■adjust the traffic forecast on the basis of the mitigating circumstances
■review the results
■test the sensitivity of the forecast
■adjust the mitigating circumstances that have been used
■revise the forecast
■estimate the design traffic data

The second technique, *rural growth analysis*, "is to be followed when four-step planning models are not appropriate (either for lack of data and/or time) and when the historical data at the project site are insufficient to allow the calculation of trends for that site. These problems usually occur on low volume, rural roads for pavement-only (resurfacing) projects. This methodology does not account well for changes in traffic growth or changes in travel patterns resulting from expected geometric changes to the project facility or surrounding facilities. It can do a reasonably good job of estimating growth due to a new housing or industrial construction in the immediate vicinity." (p 88.) The third technique, the *four step modeling process*, is to be followed when you select any of the four-step computer models." It is clearly the most data and time intensive of any of the procedures available.

Chapter 6 provides "...a description of the reviews that a forecast should undergo before being used as design information by the Department.... The reviews that should be performed for all traffic forecasts include: (1) reviews within the forecasting office, (2) reviews within the department, but outside of the office that creates the forecast, and (3) reviews outside of the WSDOT.

This study is clearly an important work and one that should serve as a useful guide for Idaho Transportation Department traffic engineers and planners. The guidelines are easy to follow and applicable to a wide range of projects. However, the guidelines do lack specific information needed to prepare the most common kind of forecast used by ITD: those based on time history data.

2.3 AASHTO DATA COLLECTION GUIDELINES

A recent report from AASHTO describes some of the issues involved in the important and related areas of data collection and forecasting. The objective of the "...Guidelines is to improve the quality of the traffic information that supports decisions at all levels of the transportation profession." Six principles are established in the Guidelines (p 8).

- The Guidelines will move toward a common traffic monitoring practice.
- The Guidelines will establish a phased program to achieve a common practice. This will include near term minimum practices and future directions.
- The Guidelines will be practical and capable of implementation.
- What is practical in the Guidelines will be directed by the need to provide quality traffic data for decision making.
- Truth-in-Data, which is the disclosure of practice and estimate of data variability, is central to the Guidelines to ensure appropriate data quality and use.
- The Guidelines will present a dynamic approach to traffic data programs. Further development will be encouraged through clarity and integrity of common practice.

The report presents useful information on forecasting. "The purpose of constructing a mathematical model is to represent the predictable behavior of a process while excluding its random characteristics. The helpfulness of any model is how well it replicates reality. In traffic simulation this typically entails comparing estimated traffic flows to average traffic counts. (p 103) "Traffic flows on roadway have two elements of variation. The first element is composed of well-documented diurnal and seasonal variations in travel. The second element is the truly random component, such as special events and weather. The predictive error of a traffic model calibrated to counts can be anticipated from the observed data. "If the variation in the summary statistic (average count) accurately portrays traffic conditions, it is an accurate measure. In order to accept a relatively imprecise average volume with, for example, a standard error of 50 percent, the analyst must be satisfied that this is the reality of travel on the street network. This is at odds with what is known about the variability of traffic in urban areas. Accordingly, such a statistic would introduce unacceptable errors for the purpose of traffic simulation. "The practical implications of accepting a statistic where the standard deviation is one-half the mean can be shown by example. Consider one lane of an urban freeway. Accepting a traffic count with a standard deviation of one-half of the mean requires us to accept any model that predicts flows ranging from 0.5 to 1.5 times the mean. Assuming the data are normally distributed, in nine out of ten observations the mean will fall in that range. This is well outside of the typically accepted one lane of error in the profession. Similarly, a standard deviation of one-fifth of the mean would be within one lane of error.

"The same wide range affects forecasts. The analyst would be forced to accept any interpretation of the results falling within the accepted interval. A travel demand simulation forecast with such a range may be meaningfully used neither for policy analysis nor roadway design.

2.4 Purdue University Forecasting Procedure

Saha and Fricker identify changes in explanatory variables over time to rural traffic volumes. "This study builds on previous effort found in the field of rural traffic forecasting. The study combines careful statistical analysis with subjective judgement to develop models that are statistically reliable and easy to use. This study developed two different kinds of models - aggregate and disaggregate - to forecast traffic volumes at rural locations in Indiana's state highway network. These models are developed using traffic data from continuous count stations in rural locations as well as data for various county, state, and national level demographic and economic predictor variables. Aggregate models are based on the functional classification of a highway, whereas the disaggregate models are location-specific. These models forecast annual average daily traffic for future as a function of present year AADT, modified by the various predictor variables.

"Estimates of future traffic can be obtained by two very different methods: trend projections and forecasts. Analysts can modify extrapolated trends based on their experience and knowledge of the route, state, or region. With trend projections only traffic data are being dealt with; in forecasting techniques, however, a relationship between traffic and explanatory factors must be established." (p. 10)

Saha and Fricker found that it is important to make forecasts for similar functional categories (e.g. rural interstate, rural principal arterial, rural minor arterial, and rural major collector) and possibly to dissagregate by geographic region in the state. For the aggregate traffic forecasting models, with average annual daily traffic as the dependent variable, Table 2 shows the variables that are the best predictors of ADT.

Table 2. Aggregate Models, Independent Variables

Functional Classification	Independent Variables
Rural Interstate	State Population
Rural Principal Arterial	County Population State Population
Rural Minor Arterial	County Households
Rural Major Collector	County Population

For the disagregate traffic forecasting models, with average annual daily traffic as the dependent variables, some of the key independent variables are listed in Table 3.

Table 3. Disaggregate Models, Independent Variables

Functional Classification	Independent Variables
Rural Interstate	State Population US Gas Price County Population
Rural Principal Arterial	State Vehicle Registrations US Gas Price County Vehicle Registrations
Rural Minor Arterial	County Vehicle Registrations US Gas Price County Employment
Rural Major Collector	County Vehicle Registrations County Employment County Population

2.5 Time Series Analysis Methodology

The problem of measuring the effects of change over time is an important one in most fields of scientific inquiry. In the physical or life sciences it is often possible to design experiments so that the necessary measurements of all factors affecting a given process can be taken. In transportation problems, however, it is usually not practical to design experiments as such. Rather, certain real-world processes must be identified as influencing factors and must then be measured as best they can.

Methodological problems are often prevalent in transportation impact studies. Typically, the analyst will collect information before and after the implementation of a change, and assert that the differences in some variable between these two points in time constitute the impact or effect of a particular change. Often, no account is taken of the character or nature of the underlying processes that might be involved. In a study of methodologies used for analyzing transportation impacts, Charles River Associates (1972) found that "... the most prevalent and fundamental shortcoming is the failure to conceive of the possibility of estimating models." (2-32) The identification and estimation of a set of models to describe the processes that are under study would allow the analyst the opportunity to view the evolution of these processes over time and deduce conclusions about their nature and impacts.

The basic classes of models have been developed by transportation analysts, cross-sectional and time-series. Each class seeks to define the nature of travel demand and the factors that influence it. Cross-sectional models are developed using data collected at one point in time. Often, intensive travel surveys are performed and detailed characteristics of the transportation system are measured. The level of detail of the data allows the development of models that are able to relate micro-level characteristics of the system. For example, characteristics of individual trip-making patterns such as traveler demographics and travel costs and time by competing modes can easily be handled with cross-sectional models. However, using these models to assist in evaluating the impacts of a change over time involves some degree of risk. It is not clear that structural relationships estimated at one point will remain stable over time. Time-series models are based upon data collected over a period of time and thus allow for direct measurement of the nature of these dynamics. The trade-off here is that the level of detail for time-series data is not nearly as great as for cross-sectional data. This reduces the precision with which time-series models can approximate true structural relationships in the data.

One of the most common methods for studying changes over time are those developed by Box and Jenkins. A number of researchers have used the time-series analysis techniques of Box and Jenkins (1976) to model changes in traffic and transit demand over time. These models can range from simple univariate relationships, where only the effects of past values of demand itself are considered, to those where complex feedback effects are considered.

Der (1977), Elder (1977), Holmesland (1979), Ahmed and Cook (1979), Nihan and Holmesland (1980), Benjamin (1986), Mahalel and Hakkert (1985), and Davis and Nihan (1984) investigated the potential of the Box-Jenkins technique for short-range traffic volume and speed forecasting. Each showed that using only univariate models could provide an effective analysis and forecasting tool.

Nihan and Holmesland (1980), for example, used monthly averages of weekday traffic in Seattle, Washington for the years 1968 through 1976 to fit a time-series ARIMA (auto-regressive integrated moving average) model. The resulting model was used to forecast volumes for the year 1977. Forecast volumes were then compared to actual volumes in 1977. The results of this study indicated that time-series techniques can be used to develop highly accurate and inexpensive short-term forecasts. The weaknesses in this approach are the large number of data points needed for estimation, the need for completeness of the data for all periods, and the required expertise of the model builder. A discussion of the ways in which such models can be used to evaluate the effects of policy changes or other outside impacts was included. Davis and Nihan (1984) used time-series analysis to detect relatively small changes in traffic flow characteristics such as peak hour volume and lane occupancy.

Benjamin (1986) presented a procedure for forecasting average daily traffic using time-series data. He compared this simple model with the UTPS developed demand forecasts and noted favorable results. He also noted that this method is much cheaper than using the traditional UTPS process. This method works well in a stable or modest growth situation, but "cannot estimate sudden shifts in behavior, changes in the transportation network, or the introduction of new modes. Often the effect of large changes is local, having little effect outside of proximate zones or traffic corridors". (52) He noted that the addition of explanatory variables to the time-series model would improve its predictive ability.

Mahalel and Hakkert (1985) presented a Box-Jenkins univariate ARIMA model for the spot speeds of vehicles on a road section. The two sections studied resulted in first-order and second-order autoregressive models, respectively, thus showing the interaction and interdependence among the vehicles. The second-order autoregressive model, for example, indicates that the speed of a given vehicle depends upon the speeds of the preceding two vehicles. The section for which the first-order model was developed had volumes less than one-quarter of the other section modeled, a result showing that there is less vehicle interaction when volumes are lower.

A number of researchers have used this class of models to study transit demand. Harmatuck (1975) and Wang (1981) used intervention ARIMA models to study the effects of intervening events such as transit strikes and fare changes on transit ridership levels.

McLeod, Everest, and Paully (1980) developed both univariate ARIMA models and transfer-function models to study air and rail passenger traffic between London and Glasglow. Jenkins, et. al. (1981) extended this work and explored the influences of fare levels, journey times, and competition effects between modes on both the East Coast and West Coast routes. The influences of petrol price, and of certain macro-economic variables were also established.

Start (1981) also described a time-series analysis of passenger flows on the Glasgow suburban rail network. His objective was to establish a modeling framework for the assessment of the effects of operational changes to the system, and the emphasis was placed upon obtaining accurate estimates of changes in patronage. The logarithm of patronage was established as the dependent variable of the model. Independent variables include real bus fare, real rail fare, seasonal factors, car costs, and disposable income.

Polhemus (1976, 1979) studied air traffic volumes using both univariate and transfer function time-series models. He considered the problem of constructing a dynamic time-series model for local fluctuations in traffic parameters from observations collected during periods when the rate of traffic flow was not constant. An ARIMA model was postulated to describe the local traffic fluctuations using an eight-hour sample of air traffic in the local control sector at New York's LaGuardia Airport. The application of high-pass filters to discrete time series of traffic indices obtained through a measurement queue is a useful procedure for separating the local fluctuations in traffic parameters from effects on a more macroscopic time scale. The techniques are applicable to any traffic system which can be viewed as a facility serving vehicles that both arrive and depart as point processes. Using the filtered series, simple and parsimonious models can be constructed to describe the dynamic behavior of the system on a local time scale. Once a model is developed, it can be used for short-term forecasting or simulation purposes.

Skinner, Waksman, and Wang (1983) used time-series revenue data from the Southern California Rapid Transit District (SCRTD) in Los Angeles as a case study to develop empirical models and forecasts of monthly transit revenue for financial planning. Seasonal time-series models for the five major types of transit revenues collected by SCRTD were constructed and estimated. In all five cases, the observed variation in revenue during the estimation period was explained well by the fitted values obtained from the models, as was demonstrated by the relevant regression statistics and the models' behavioral characteristics. A data split technique was used to determine the models' prediction capabilities. A comparison of the forecasts with the actual data shoed the models to perform well for forecasting purposes. Finally, the models were used in a simulation mode to estimate the revenue impacts of SCRTD's June 1982 fare rollback for the next year and a half following the rollback.

Wang, Maling, and Skinner (1982) presented empirical models of monthly ridership for seven U.S. Transit Authorities. Within the framework of these models, the impacts upon monthly ridership from changes in the real fare and gasoline prices were examined. They found that the elasticities of monthly transit ridership with respect to the real fare were negative and inelastic, and the elasticities of monthly transit ridership with respect to the real gasoline price were positive and inelastic. Such results have important policy implications for decisions based on the relationships of price, revenue, and ridership, and for assessing the impacts of changing gasoline prices upon urban model choice.

Wolfgram and Harmatuck (1982) utilized a multiple time-series framework to identify and estimate models of monthly gasoline consumption in Wisconsin. A comparison of forecasts produced by existing econometric specifications with forecasts produced by univariate and transfer function models clearly showed the superiority of the latter approaches.

Kyte, Stoner, and Cryer describe a technique for studying changes in travel demand over time based on time-series analysis. While this study focused on transit ridership, the method has been applied to a variety of traffic demand studies. They describe the "... development and application of a methodology to identify and analyze the factors that influence changes in public transit ridership. The data used in the model development and testing are from Portland, Oregon... The statistical approach used here was developed by Box and Jenkins for time series data. ... Of particular interest here is the identification of the lag structures and functional forms that constitute the relationships between transit ridership, level of service, travel costs, and market size." (abstract)

2.6 Other Demand Forecasting Methodologies

Khisty and Rahi use a simplified application of the standard four-step travel demand forecasting process. They note that "...conventional urban travel demand models, which are data-hungry, costly, and mainly mean for use in large cities and metropolitan areas, are not suitable for small urban areas with a population of 500,000 or less. These small urban areas generally lack the staff, expertise, and budget to operate the conventional models. Three simplified travel demand models are evaluated that are suitable for small urban areas and make use of routinely collected ground counts." All four models are simplified applications of trip interchange calculations based on ground counts.

Poole and Newnam describe another application of the four step process. "A procedure for synthesizing travel movements in small and medium sized urban ares ... is described. Four methods are used, depending on the extent of travel surveys done as part of the transportation study." All four methods require some synthesis of OD travel patterns. Each also requires comprehensive traffic volume counts, and inventories of employment, commercial vehicles and dwelling units. Data are used as part of the standard four step process.

Middleton and other looked at trip generation characteristics of truck traffic. "Special-use truck traffic is the traffic associated with the processing and transporting of timber, grain, beef cattle, cotton, produce, sand and gravel, and limestone. Industry and vehicle characteristics for each of these six commodities were determined. The impact of each special-use activity center was assessed in terms of trip generation. Specific activity center were selected for each industry. Number of trips generated, radius of influence, loads, vehicle configuration, and seasonal variations were determined for each selected activity center through agency and industry contacts and field studies." The study focused on trip generation rates for each category described above.

CHAPTER 3. CHANGES IN TRAFFIC VOLUMES ON IDAHO HIGHWAYS

3.1 Introduction

One of the most important tasks in demand forecasting is to develop an understanding of the historical trends of the variable to be forecast and to identify and study the factors that might have contributed to these trends. How do the volumes vary by region of the state, by highway classification, or by area served (i.e. urban vs rural)? The study by Saha and Fricker cited in Chapter 2 stated the importance of these analysis categories.

In the next chapter, some of these underlying causal factors are explored. In this chapter, a history of traffic volume trends on Idaho highways is presented. Both total traffic volumes as well as truck traffic volumes are presented.

3.2 Automatic Traffic Recording Stations

The Idaho Transportation Department has a system of Automatic Traffic Recorders, or ATR's, located on highways throughout the state. From this system, ITD has developed an extensive data base for average daily traffic volumes for each month going back to January 1970, and, in some cases, even earlier.

The ATR system includes a total of 107 stations that are currently actively collecting traffic volume data. Table 4 shows the distribution of ATR stations by ITD District. A complete list of the ATR stations is given in Appendix A.

Table 4. ATR Stations by District

District	Number of ATR Stations
1	12
2	8
3	45
4	8
5	20
6	14

Tables 5 and 6 show the number of ATR stations by highway functional classification. Each functional category is adequately represented. Nearly two-thirds of the stations are located in rural areas, while about one-third are located in urban areas.

Table 5. ATR Stations By Functional Classification

Functional Classification		Number of ATR Stations
Urban	Interstate	8
	Principal Arterial	13
	Minor Arterial	15
	Collector	4
Rural	Interstate	13
	Principal Arterial	29
	Minor Arterial	15
	Major Collector	10

Functional Classification	Number of ATR Stations
Interstate	21
Principal Arterial	42
Minor Arterial	30
Collector	14

Table 6. ATR Station by Urban/Rural Area

Area Served	Number of ATR Stations
Urban	40
Rural	67

The ATR stations have, in most cases, provided a reliable and extensive time history of traffic flow data. Table 7 shows that nearly three-fourths of the stations have monthly data for at least the past fifteen years. This quantity of data is clearly an important element in the development of traffic forecasting tools.

Table 7. Size of Data Base for ATR Stations

Begin Period	End Period	Number of Consecutive Monthly Counts	Number of ATR Stations
Jan-70	Dec-90	252 (21 yrs)	54
Feb-70/Jan-76	Dec-90	180-251 (15-21 yrs)	23
Feb-76/Jan-81	Dec-90	120-179 (10-15 yrs)	10
Feb-81/Jan-86	Dec-90	60-119 (5-10 yrs)	5
Feb-86	Dec-90	<60	15

3.3 Traffic Volume Growth Rates

Tables 8 through 12 present a summary of traffic growth rates for Idaho highways. These tables show the varying growth rates according to ITD District, functional classification of the highway, and area served.

During the decade of 1980, the annual growth rate on state highways averaged 1.9 percent per year. The growth rate was nearly double this rate in the latter half of the decade, averaging 4.1 percent per year. ITD Districts 1, 3, and 4 had the highest growth rates, each at nearly five percent per year during the period 1985 through 1990. Appendix B provides a more detailed summary of traffic growth rates on Idaho highways.

Table 8. Overall Growth Rates for Idaho Highways

Period	Annual Growth Rate
1980-1990	1.9%
1985-1990	4.1%
1988-1990	1.6%

Table 9. Growth Rate by Highway District

Highway District	Annual Growth Rate		
	1980-1990	1985-1990	1988-1990
1	3.4%	4.7%	1.6%
2	0.9%	2.9%	-2.7%
3	2.8%	4.7%	2.7%
4	1.9%	5.0%	-3.0%
5	0.7%	2.0%	-1.0%
6	1.3%	4.3%	2.6%

Traffic growth rates varied somewhat by functional highway classification. Urban interstate highways showed the highest growth during the 1980's. During the last half of the decade, average annual growth rates ranged from 2.6% on urban and rural minor arterials to 6.6% on urban interstate highways.

Table 10. Growth Rate by Functional Category

Functional Category		Annual Growth Rate		
		1980-1990	1985-1990	1988-1990
Urban	Interstate	4.7%	6.6%	2.9%
	Principal Arterial	2.2%	3.5%	0.5%
	Minor Arterial	1.3%	2.6%	-1.8%
	Collector	-	2.9%	5.1%
Rural	Interstate	2.0%	4.0%	0.0%
	Principal Arterial	1.7%	4.4%	2.3%
	Minor Arterial	1.3%	2.6%	-1.5%
	Major Collector	2.9%	4.9%	5.3%

Urban and rural facilities experienced approximately the same growth rates during the last half of the 1980's, though urban highways had a slightly higher rate over the course of the entire decade.

Appendix C provides a time plot of the monthly average daily traffic for each ATR station.

Table 11. Growth Rate by Functional Category

Functional Category	Annual Growth Rate		
Interstate	3.2%	5.1%	1.2%
Principal Arterial	1.8%	4.2%	1.9%
Minor Arterial	1.3%	2.6%	-1.6%
Collector	2.9%	4.7%	5.3%

Table 12. Growth Rate, Urban vs Rural

Category	Annual Growth Rate		
Urban	3.0%	4.1%	0.5%
Rural	1.8%	4.0%	1.5%

3.4 Automatic Traffic Recorder Stations For Truck Traffic

Thirty-eight ATR stations have been recording truck traffic volumes, some since 1984. The number of ATR stations in each ITD District is given in Table 13.

Table 13. ATR Stations by ITD District

District	Number of ATR Truck Stations
1	4
2	4
3	9
4	3
5	7
6	8

Tables 14 and 15 show the number of ATR truck stations by functional highway classification and area served. As might be expected, the majority of truck counting stations are on either interstate highways or principal arterials, areas in which truck traffic is relatively high. Nearly all truck counting stations are on rural highway facilities.

Table 14. ATR Stations by Functional Classification

Functional Classification		Number of ATR Truck Stations
Urban	Interstate	2
	Principal Arterial	1
	Minor Arterial	0
	Collector	0
Rural	Interstate	11
	Principal Arterial	13
	Minor Arterial	4
	Major Collector	4

Functional Classification	Number of Truck ATR Stations
Interstate	13
Principal Arterial	14
Minor Arterial	4
Collector	4

Table 15. Truck ATR Stations by Area Served

Area Served	Number of ATR Stations
Urban	3
Rural	35

Truck volume data is available for at least five consecutive years for 40 percent of the ATR stations. This distribution of the size of the data base available by station is given in Table 16.

Table 16. Size of Truck Volume Data Base

Begin Period	End Period	Number of Consecutive Monthly Counts	Number of ATR Stations
Jan-86 or before	Dec-90	> 60	1
Feb-86/Jan-88	Dec-90	48 - 59	14
Jan-88 or after	Dec-90	< 47	23

3.5 Truck Volume Growth Rates

The growth of truck traffic on Idaho highways has been steady during the past several years. For the ATR stations for which data are available, truck traffic has increased 1.9 percent per year since 1988. Table 17 shows the annual growth rate for each ITD District. Note that for some districts, the sample size is relatively small. Thus, it is difficult to draw conclusions regarding the differential growth rates by district from these data.

Table 17. Truck Growth Rate by Highway District

District	Annual Growth Rate
1	8.6
2	-36.4
3	7.3
4	0.7
5	-1.3
6	3.0

Tables 18 and 19 show the average annual growth rate in truck traffic by functional highway classification and by area served. Again, the small sample size precludes any significant conclusions of differential growth rates by functional category or area served.

Appendix D includes time plots of average daily truck traffic flow for ATR each station.

Table 18. Truck Growth Rate by Functional Category

Functional Category	Growth Rate
Interstate	0.5%
Principal Arterial	5.7%
Minor Arterial	-6.8%
Collector	12.5%

Table 19. Truck Growth Rate, Urban vs Rural

Category	Growth Rate
Urban	-6.0%
Rural	2.5%

3.6 Vehicle Stream Composition

In addition to studying the changes in both total traffic and truck traffic over time, it is also useful to consider the relative proportion of truck traffic in the traffic stream. Eight ATR stations provided sufficient data for both total traffic and truck traffic for a study of the relative change in truck traffic as a proportion of total traffic. Table 20 provides a summary of these data.

Five of the eight stations listed in Table 20 are Interstate highways. Trucks constitute an average of 27 percent of the total traffic on Interstate highways. Trucks constitute a significantly lower proportion of the traffic stream on the other types of facilities.

The monthly variation of the proportion of trucks in the traffic stream is shown in Appendix D. Note that the seasonal variation in stream composition is particularly evident for stations 30 and 72. Both stations are along rural interstate highways. But in nearly all cases, the mean value of the truck proportion, when corrected for seasonal variation, is constant. This indicates that while truck traffic is increasing in total numbers, it has not increased as a proportion of total traffic volumes.

Table 20. Proportion of Trucks in the Traffic Stream

ATR Station	Classification	Mean Percent Trucks
4	Rural Interstate	16.5%
5	Rural Collector	3.6%
7	Rural Interstate	25.7%
25	Rural Interstate	23.7%
27	Rural Minor Arterial	7.9%
30	Rural Interstate	38.4%
60	Rural Principal Arterial	26.3%
72	Rural Interstate	31.2%

3.7 Overall Conclusions and Implications For Forecasting

There is an extensive array of ATR stations throughout the state that have provided a data base for total traffic and truck traffic extending back, in some cases to the early 1970's. Total traffic data are available for at least fifteen years (or 180 consecutive months) for 77 ATR stations. Average daily truck traffic is available for at least four consecutive years for fifteen ATR stations. This chapter has presented an assessment of some of the trends that are evident in these data.

Average Daily Traffic Growth Rates

- Average daily traffic on state highways increased at an annual rate of 1.9 percent during the period 1980 through 1990.
- Average daily traffic on state highways increased at an annual rate of 4.1 percent during the period 1985 through 1990.
- Average daily traffic on urban interstate highways showed the highest growth rates during the 1980's, averaging 4.7 percent per year.
- Average daily traffic on urban highways increased at a somewhat higher rate than for rural highways.
- On nearly every highway segment studied, there are both significant annual trends as well as seasonal variations.

Average Daily Truck Traffic

- Average daily truck traffic increased an average of 1.8 percent per year since 1988.
- On nearly every highway segment studied, there are both significant annual trends as well as seasonal variations.

Traffic Stream Composition

- The proportion of trucks on the highway segments studied remained constant, except for seasonal variation.
- Truck traffic composition is the highest on interstate highways, with trucks accounting for an average of 27 percent of the total traffic.

CHAPTER 4. CHANGES IN OTHER FACTORS OVER TIME

4.1 Overview

In order to both understand as well as be able to explain changes in traffic volumes over time, it is important to identify those factors that effect travel demand as well as to study how they have varied over time. Three variables are proposed as explanatory variables: travel cost, accessibility to the highway system, and size of travel market. In this chapter, four such explanatory variables are discussed: gasoline price as a surrogate for travel cost, vehicle registrations and gasoline consumption for accessibility to the system, and employment for market size.

4.2 Gasoline Price

The cost of travel is one of the factors that effects the number of trips that are made in a particular area or on a given facility. Some kinds of trips, such as recreational or other non-required trips, are more sensitive to gasoline price. Other kinds of trips, such as goods and mateials shipments, may also be mode-price dependent. Finally, some trips, such as work trips, are also mode price-dependent and might tend to shift to or from public transportation as relative travel costs change, if such service is available.

While monthly gasoline price data were not available for any of the regions within the State of Idaho, data for several western regions of the United States were available. The data used in this study are averaged from several western states as compiled by the United States Bureau of Labor Statistics. Figure 1 shows the monthly time trend for gasoline price per gallon for this area.

During the period 1985 through 1990, gasoline price per gallon decreased by 15.9 percent.

4.3 Gasoline Consumption

Gasoline consumption data were provided by the Idaho Transportation Department, Economic Forecasting Section. These data are summarized in Figure 2.

During the period 1985 through 1990, gasoline consumption increased by 15.9 percent within the State of Idaho. Note, by comparison with data from the section above, that gasoline prices decreased by this same percentage during this period.

4.4 Vehicle Registration

Monthly vehicle registration data for each county within the state were provided by the Idaho Transportation Department. An example is given for Ada County in Figure 3. While these data do show the trends of increasing population that come with larger volumes of vehicle registration, their use as monthly variables might be questionable since re-registrations are usually unrelated to new vehicle purchases or actual population increases. However, the variable does provide at least a general indicator over time of the level of economic activity and the size of the population base.

4.4 Employment

Employment data are gathered monthly by the State of Idaho. Four variables are tracked: total employment-unadjusted, total employment-adjusted, civilian labor force-unadjusted, and civilian labor force-adjusted. An example time trend for Ada County employment for these four variables are given in Figures 4 through 7.

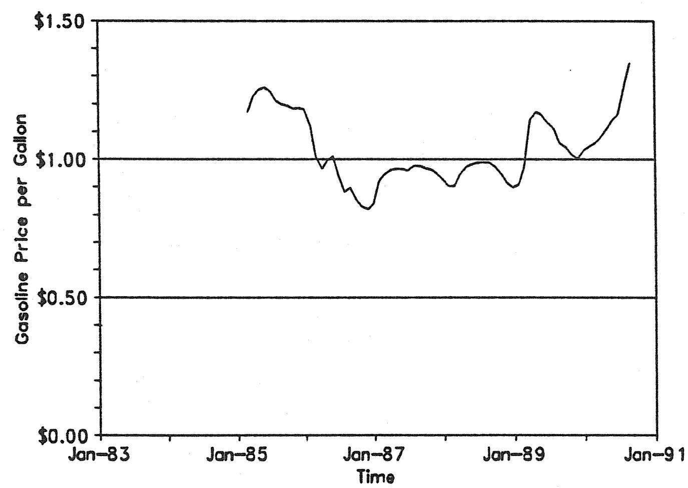

Figure 1. Gasoline Price Variation

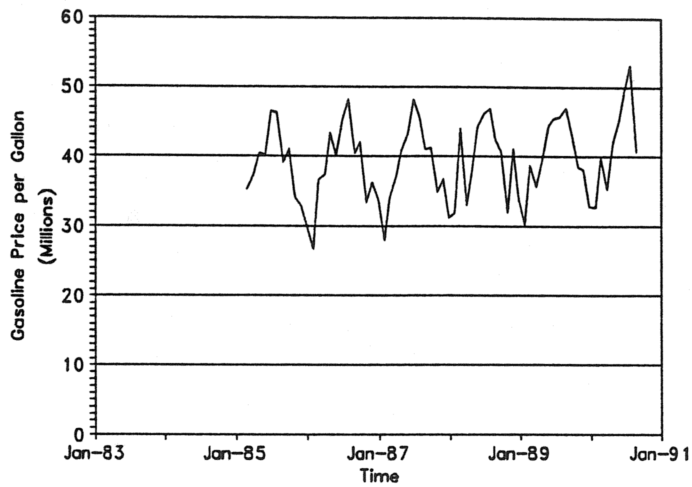

Figure 2. Gasoline Consumption, Statewide Data

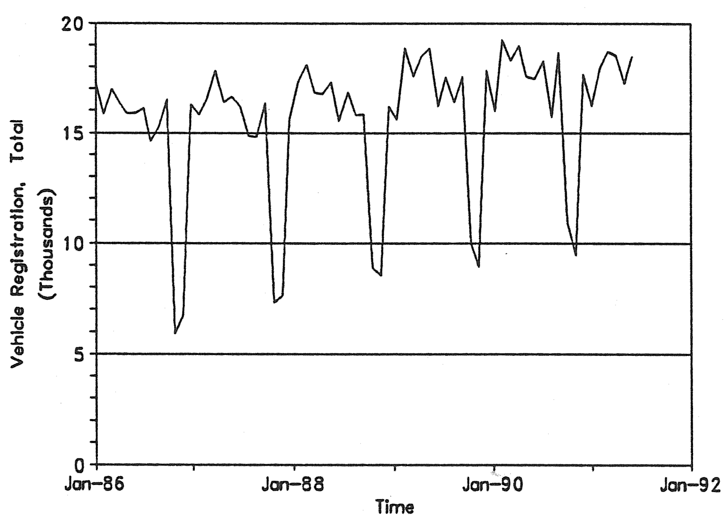

Figure 3. Vehicle Registrations, Ada County

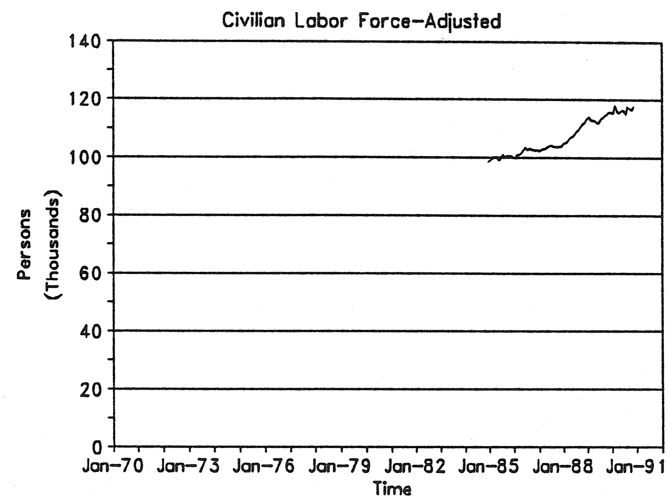

Figure 4. Adjusted Civilian Labor Force, Ada County

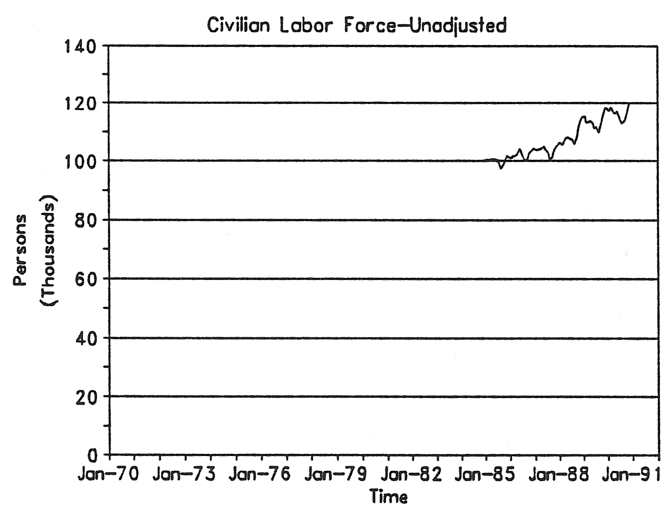

Figure 5. Unadjusted Civilian Labor Force, Ada County

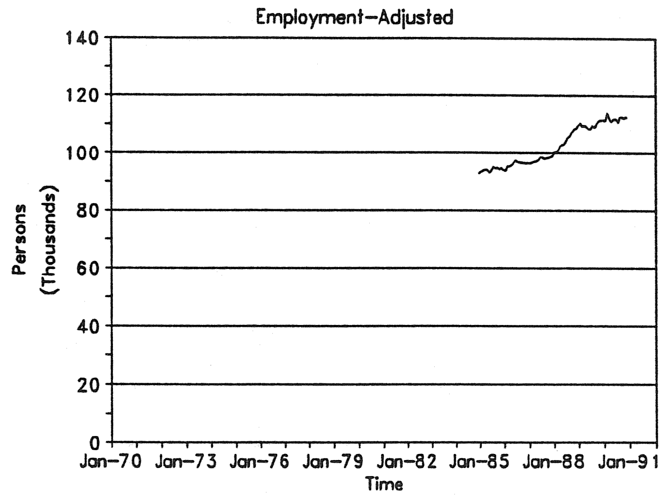

Figure 6. Adjusted Employment, Ada County

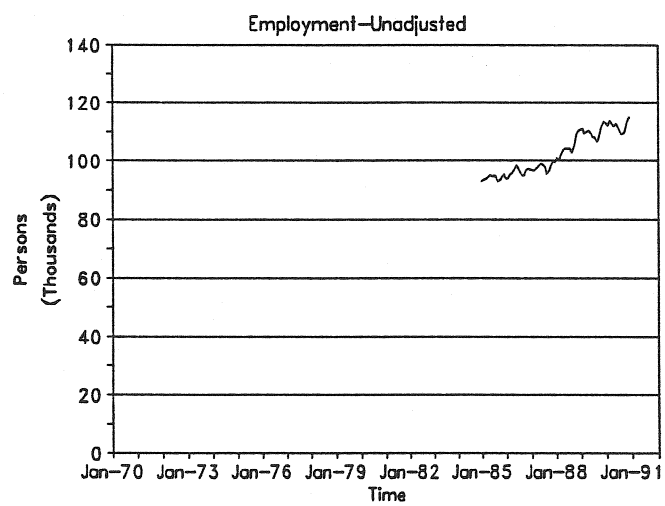

Figure 7. Unadjusted Employment, Ada County

CHAPTER 5. DEVELOPING A TIME SERIES DEMAND MODEL

5.1 Overview

The purpose of this chapter is to describe the process for developing both a univariate and multivariate (transfer function) traffic demand model. This statistical material presented here is somewhat technical and need not be read by the general reader. The data files needed to estimate the models and develop the forecasts are also presented and are probably of more general interest.

The overall objective here is to develop models to forecast monthly ADT (total traffic) using univariate time series models and transfer function time series model and to forecast monthly ADT (truck traffic) using univariate time series models.

5.2 Travel Demand

Mannheim (1979) described the transportation demand function as a "... representation of human behavior which can be used to predict how individuals or firms, or groups of individuals or firms, will change transportation choices in response to changes in future conditions." There are a number of attributes that face travelers as they make choices on trip destination, trip times, travel route, and travel mode. These include travel time, user cost, safety, comfort, and convenience. While safety, comfort, and convenience may be difficult to quantify for modeling and analysis purposes, time and cost are relatively easy to quantify. Travel time and cost can also be analyzed into components that need to be considered separately. For example, travel time can include total trip time, reliability (variance in trip time), transfer time, frequency of service, and schedule times. And, the user must consider simultaneously these attributes for each available mode (e.g. auto, bus, walking) as a travel choice or decision is made.

A demand function is essentially a characterization of the activity system (i.e. the set of consumers and the activities in which they may engage) and the transportation system with its set of service attributes which together allow a forecast of the number of users (or volume) for a given transportation service. Mannheim also noted that the activity system may be characterized in terms of population, employment, income, family size, or other similar variables. The transportation system can be described, as mentioned above, in terms of time, cost, safety, comfort, and convenience.

The demand function that is hypothesized here includes attributes of both the activity system and the transportation system. Ideally such a function would consider service and cost attributes of all available transport modes. Demand would then be a function of the activity system (population, employment, income, etc.), system attributes of the automobile or highway system (cost, time, safety, comfort, and convenience), system attributes of the public transportation system (cost, time, safety, comfort, and convenience), and system attributes for other available transport modes.

5.3 A Time-Series Travel Demand Function

A travel demand function sensitive to changes over time is of major interest here. Such a demand function must consider highway demand or usage as the major output and it must consider the following factors as inputs: (1) level of accessibility, (2) relative costs of travel, and (3) the level of travel generating activity in the area under study. In addition, there are three issues that are relevant to the nature of the functional relationships involved here: the level of response to change, the time-delay or lag of the response to change, and the feedback that may exist between the variables.

5.4 Lagged Consumer Response

Changes in accessibility, travel costs, or market size do not instantaneously result in changes in traffic demand. It usually takes time for highway users to hear about or perceive a change in the level of accessibility, for example, and then make decisions about whether to change their pattern of travel. For this reason, the function relating travel demand to changes in the independent variables must include these lag effects. These delay or lag effects are an important behavioral component in general to consumer response to changes in the marketplace. For example, Heyse and Wei (1985) note that "it has been demonstrated that a strong relationship between sales and present and past advertising exists. Such lagged advertising effects on sales may result from delayed response to the marketing effort, or to a holdover of new customer demand or to an increase in demand from existing customers, In addition, advertising may have a cumulative effect on demand."

An analogy may be drawn between this relationship and the one that exists between transit demand and service level, for example. Alperovich, Kemp, and Goodman (1977) note that one "of the attractions of using time series data in an analysis of transit demand is that they afford the opportunity to explore hypotheses concerning the time profile of the demand response to service or price changes. It seems likely that demand would adjust instantaneously, even when instantaneously implies a one month time period. One might expect the response to a fare change, particularly a fare increase, to be more immediate than the response to a service adjustment. Fare increases typically attract greater coverage in the news media than all but the most radical or the most flamboyantly promoted service change. Moreover, existing patrons are aware of the fare change from the day it is instituted, whereas it may take them much longer to become fully aware of schedule adjustments."

5.5 Methodology

The statistical methodology that has been used in this research was developed by Box and Jenkins (1976). This approach is based upon the philosophy that models should be parsimonious (i.e. represented with the smallest possible number of parameters) and that model building should be iterative. That is, there is a logical sequence of steps and checks that should be followed when constructing a model and which may need to be repeated until a satisfactory model results. These steps include identification of a tentative model based upon various statistics constructed from the data itself, estimation of parameters for the tentatively identified model, and diagnostic checking for model adequacy. One of the most important aspects of this approach is that the form of the model is not assumed in advance but is based directly upon the data. While theory may provide some guidance regarding which variables to include and the signs of the model coefficients, the analyst must look to the data for clues regarding the lag structure of the independent variables and the error structure of the model.

There are five classes of time-series models. The simplest, the univariate model (U), relates the current value of a time series to a combination of its past values and random shock (error) terms. Next, intervention (I) and transfer function (TF) models relate a dependent variable to independent variables (or input series) that directly effect the dependent variable (or output series). These models may also include error or shock terms. Multiple time series (MTS) models and simultaneous equations transfer function (STF) models involve a set of interrelated variables as well as random error terms.

Univariate Models. The simplest class of time-series models proposed by Box and Jenkins is the univariate autoregressive-integrated-moving average (ARIMA) model which can be written:

$$\phi_p(B)(1 - B)^d z_t = \theta_q(B)a_t \tag{3}$$

where z_t is the time-series under consideration, ϕ is the autoregressive polynomial function, θ is the moving average polynomial function, B is the backshift operator, and a_t is the error term or random shock.

Tentative models are estimated by analysis of the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the given series z_t. The ACF is the correlation between two measured observations z_t and z_{t+k}, k time periods apart. The PACF can be described qualitatively as the autocorrelation that exists between z_t and z_{t+k} after all of the intervening correlation has been accounted for. The characteristics of the ACF and PACF provide the guidelines for selecting an AR, an MA, or mixed ARMA process for a given set of data. For example, a pure moving average process of order one has an ACF that is non-zero at lag one and zero for all other lags, and a PACF that dies out exponentially for increasing lags.

Also of interest in the univariate case is the seasonal multiplicative model which has the form:

$$\phi_p(B)\Phi_P(B)(1 - B)^d z_t(1 - B^s)^D = \theta_q(B)\Theta_Q(B)a_t \tag{4}$$

where ϕ, θ, and d are the non-seasonal components of the model, Φ, Θ, and D are the seasonal components of the model, and s is the seasonal period.

Transfer Function Models. The next class of models include the transfer function models. Transfer function models are of the form:

$$Y_t = \frac{\omega_i(B)B^{b(i)}}{\delta_i(B)}X_{it} + \frac{\theta(B)}{\phi(B)}a_t \tag{5}$$

where Y_t is the output series, ω and δ are the functional components of the transfer function model, b is the delay for the ith series, X_{it} are the input series, and θ and ϕ are the functional components of the ARIMA noise model. It should be noted that a one-way relationship is assumed between X_{it} and Y_t; that is, X_{it} may cause changes in Y_t, but not vice-versa.

5.6 Model Estimation and Forecasting Using SAS Software

Table 21 shows the setup for a sample model idenfication, estimation, and forecasting using the SAS software system.

Table 21. SAS Data File for Transfer Function Model

```
PROC ARIMA DATA = dataset;

     /*  STUDY THE CORRELATION FUNCTIONS                   */
     IDENTIFY VAR = VOLUME(1,12);

     /*  ESTIMATE THE UNIVARIATE MODEL                     */
     ESTIMATE Q = 1,12

     /*  FORECAST FUTURE VALUES OF VOLUME                  */
     FORECAST LEAD = 12
```

Table 22 shows the setup for a sample model idenfication, estimation, and forecasting using the SAS software system.

Table 22. SAS Data File for Transfer Function Model

```
PROC ARIMA DATA = dataset;

     /*  STUDY THE CORRELATION FUNCTIONS OF THE INPUT */
     /*  PROCESS, EMPLOYMENT                          */
     IDENTIFY VAR = EMPLOYMENT(1,12);

     /*  ESTIMATE THE MODEL FOR THE INPUT PROCESS     */
     ESTIMATE Q = 1,12

     /*  STUDY THE CORRELATION FUNCTIONS OF THE OUTPUT*/
     /*  PROCESS, VOLUME                              */
     IDENTIFY VAR = VOLUME (1,12);

     /*  ESTIMATE THE TRANSFER FUNCTION MODEL WITH    */
     /*  EMPLOYMENT AS THE INPUT VARIABLE WITH A ONE  */
     /*  MONTH LAG                                    */
     ESTIMATE Q = 1,12 INPUT = (1$(1,12)EMPLOYMENT)

     /*  FORECAST FUTURE VALUES OF VOLUME             */
     FORECAST LEAD = 12
```

CHAPTER 6. UNIVARIATE TIME SERIES MODELS

6.1 Overview

In this chapter, univariate time series forecasting models for both total average daily traffic and for average daily truck traffic are developed and presented. Time series modeling allows for a high degree of flexibility in the form of the model. The model development process ensures that the characteristics of a particular data set are reflected in the parameterization of the model that is ultimately developed to represent the data.

6.2 Forecasting Total Average Daily Traffic

As it turned out, a standard form was found to best represent both the total average daily traffic and average daily truck traffic data sets here. This model form, a seasonal univariate ARIMA model, relates the change in traffic from the previous month and the previous year to error terms that reflect both this monthly and annual variation. Thus both the seasonal components and trend components are accounted for implicitly in the models.

The model form can be represented as follows, if V_t is the daily traffic for month t.

$$V_t = V_{t-1} - V_{t-12} + V_{t-13} + (1 - \theta_1 B)(1 - \theta_{12} B^{12})e_t \qquad (6)$$

Univariate time series models were developed for thirteen ATR stations, each with 252 monthly data points. The models were estimated using 192 data points. Forecasts were then made with each model and compared with the remaining 60 monthly data points. The model parameters and forecasts are given in Table 23.

The mean absolute percent error for the monthly forecasts covering a five year or sixty month period are shown in the table. The errors range from 3.3 percent to 17.0 percent. This represents a very good level of error over a five year period. The individual forecasts and actual values are given in Figures 8 through 20.

In general, the Figures show that the forecasts track the actual measured volumes closely, even with the wide monthly or seasonal variation. For several cases, station 25, for example, there appeared to be some anomaly in the historical traffic counts themselves. The anomaly was then propagated ahead into the forecast, causing some discrepancy between the actual values and the forecast values.

Table 23. Univariate ADT Model Coefficients and Forecasts

Station	θ_1	θ_{12}	R^2	RSE	MAPE
2	.19	.64	.95	.00041	17.0%
4	.38	.57	.98	.00029	3.3%
5	.01	1.00	.79	.00033	-
10	.44	.57	.92	.00028	13.9%
25	-.01	1.00	.91	.00058	-
27	.50	.26	.87	.00853	11.8%
30	.21	.77	.96	.00017	14.8%
52	.88	.10	.94	.00032	8.9%
60	.42	.44	.97	.00015	9.9%
62	.25	.74	.97	.00065	13.5%
202	.12	.59	.30	.00001	8.2%
263	.52	.97	.99	.00063	-
266	.43	.67	.96	.00088	6.8%

θ_1 and θ_{12} are the ARIMA model parameters.
R^2 is the correlation coefficient.
RSE = Residual Standard Error.
MAPE = Mean Absolute Percent Forecast Error.

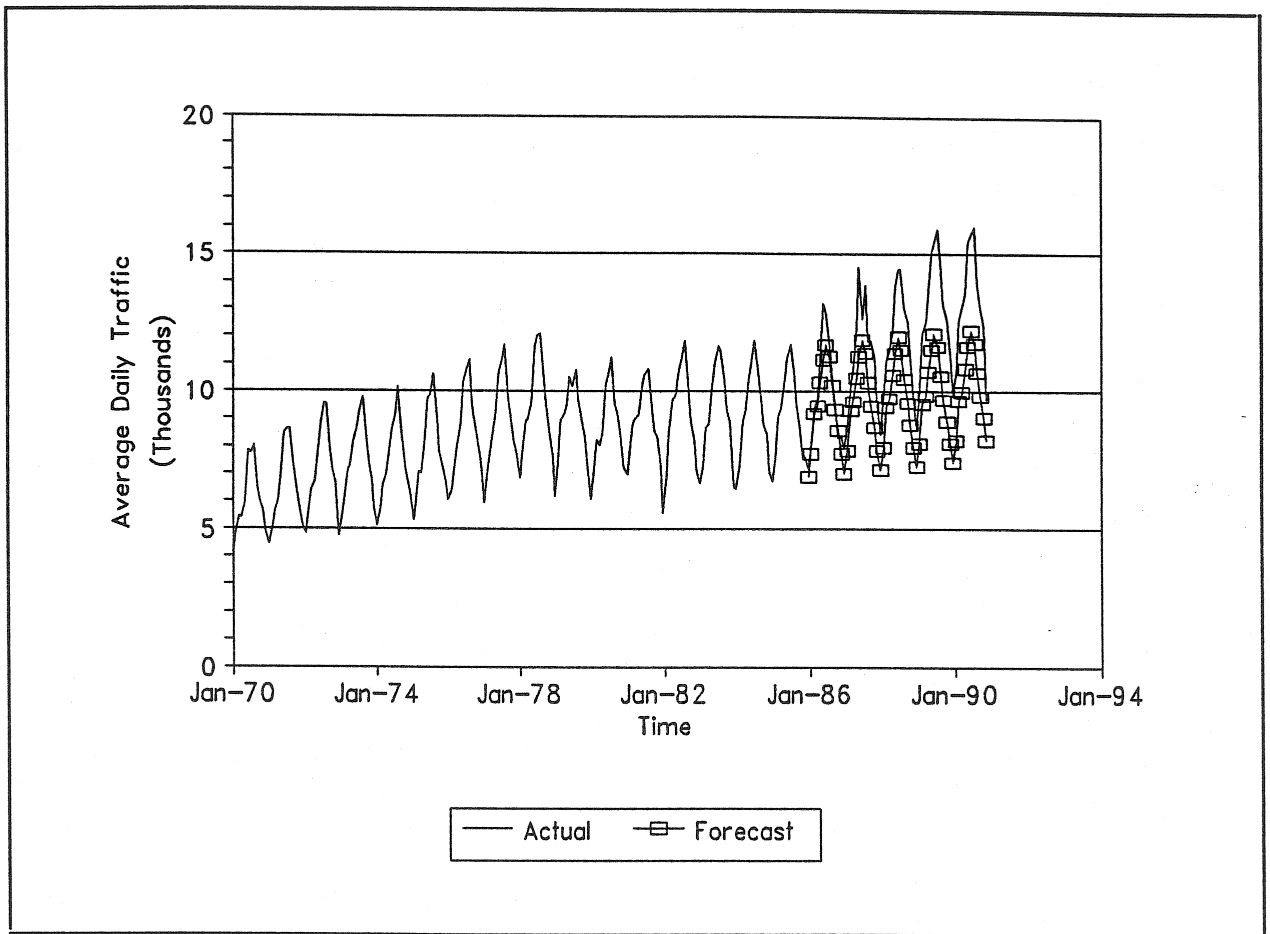

Figure 8. Station 2. Jeans Place

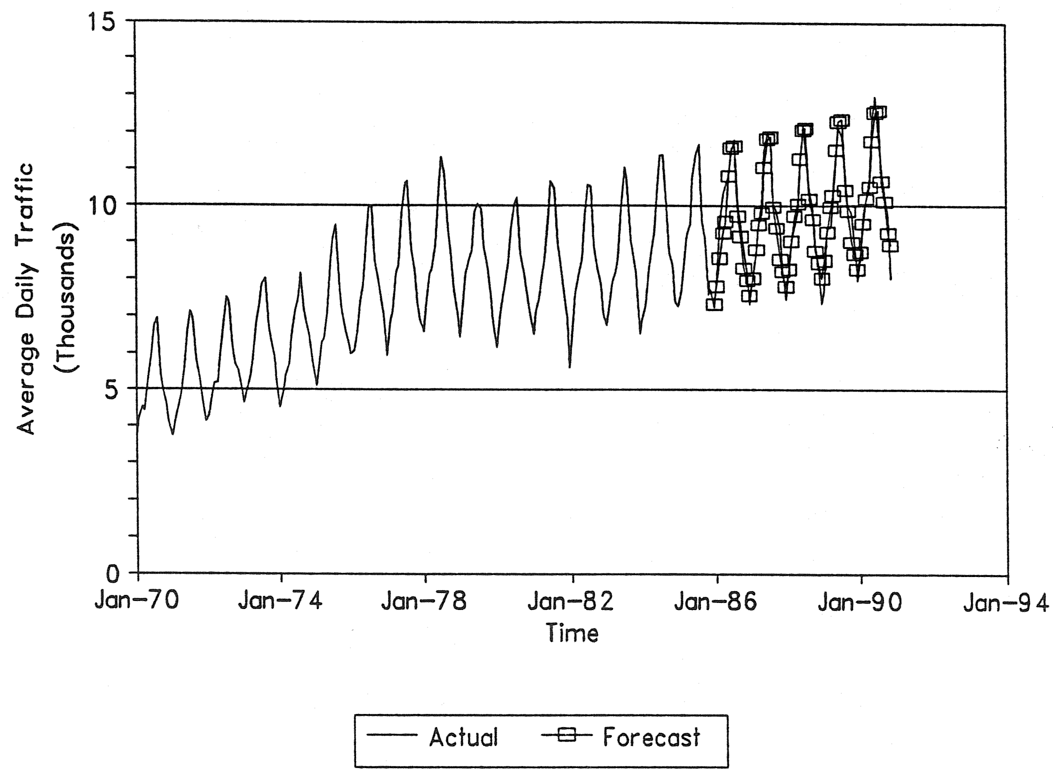

Figure 9. Station 4. South Pocatello

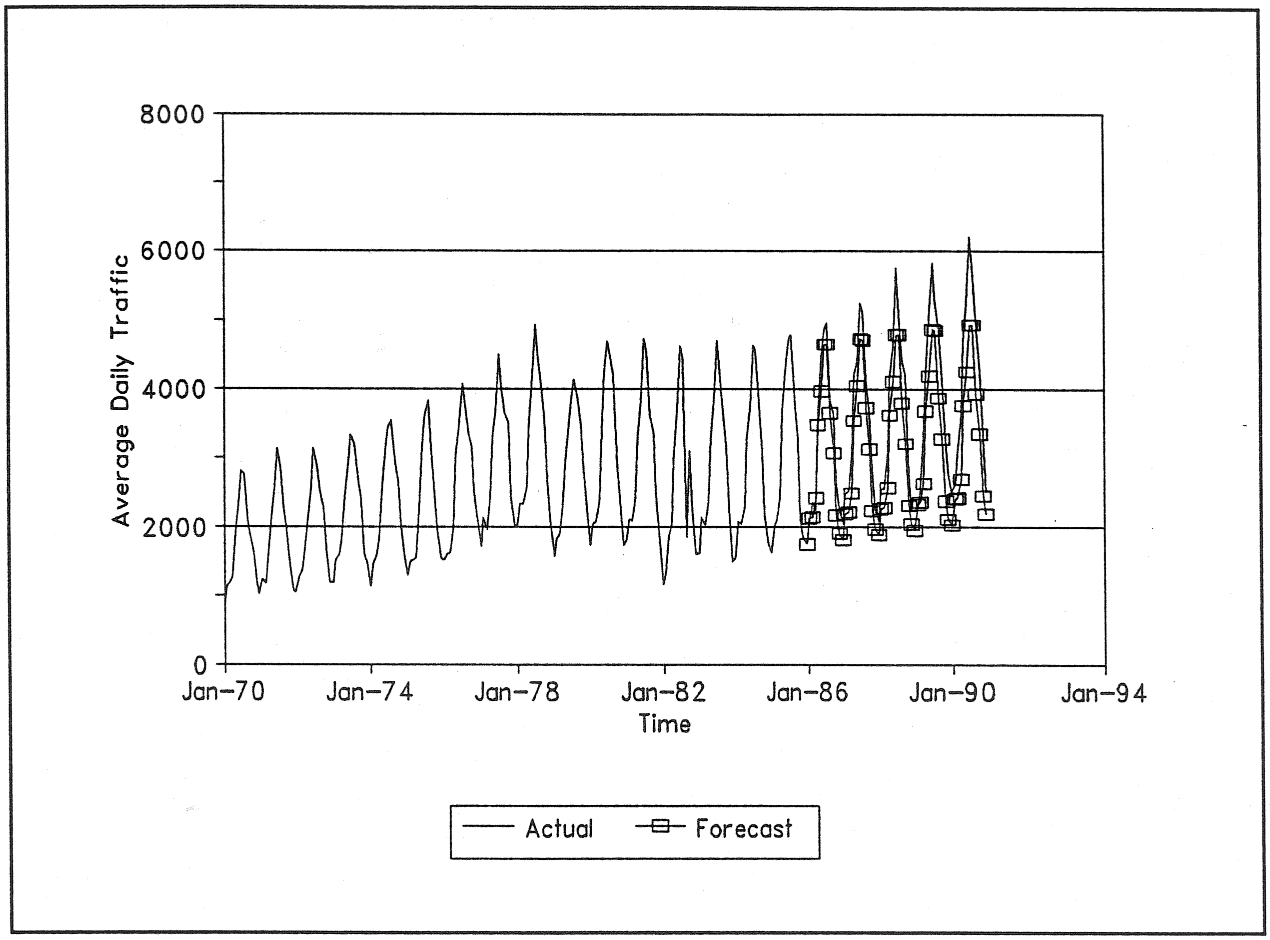

Figure 10. Station 10. Dry Creek

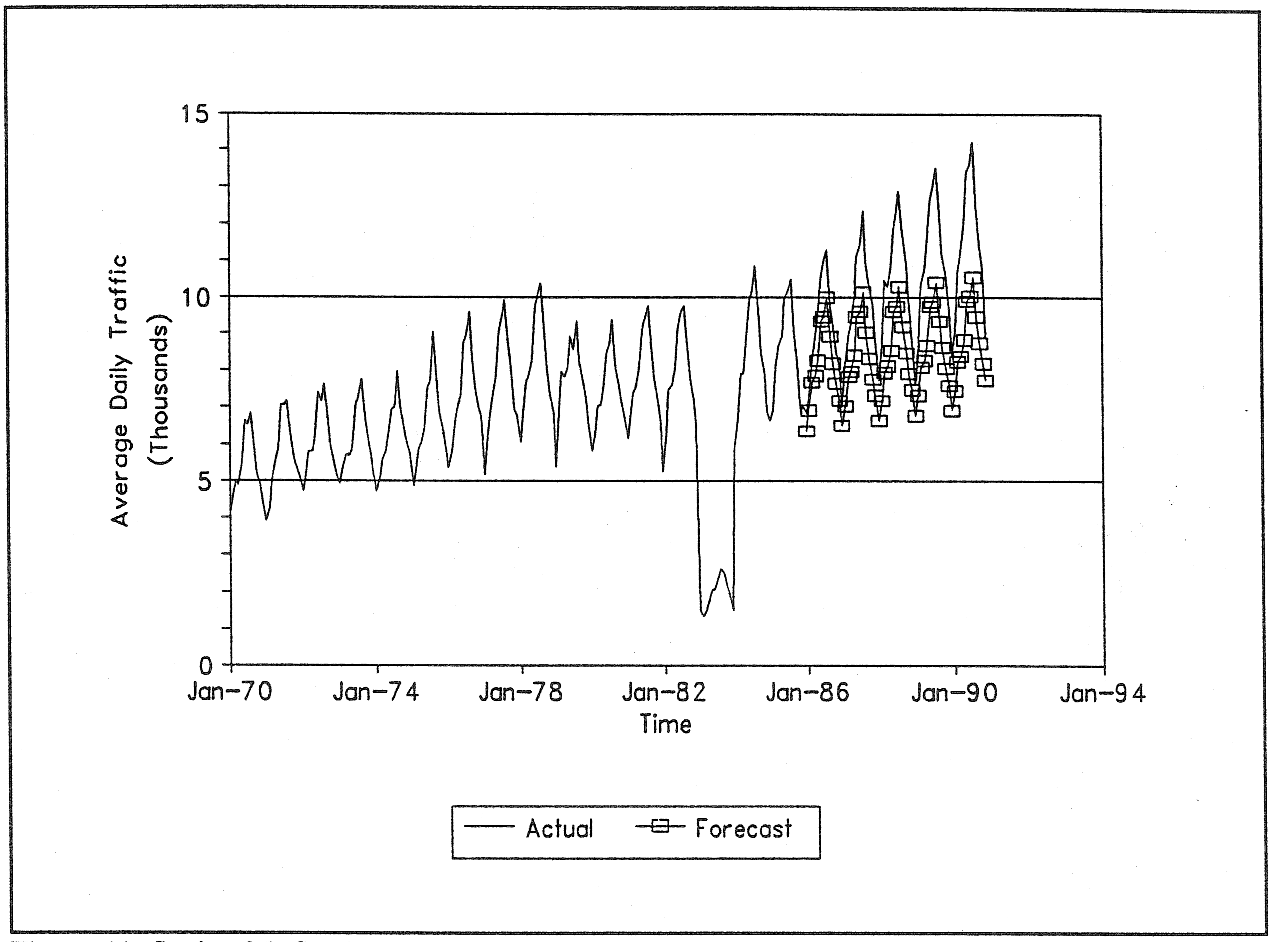

Figure 11. Station 25. Sand Hollow

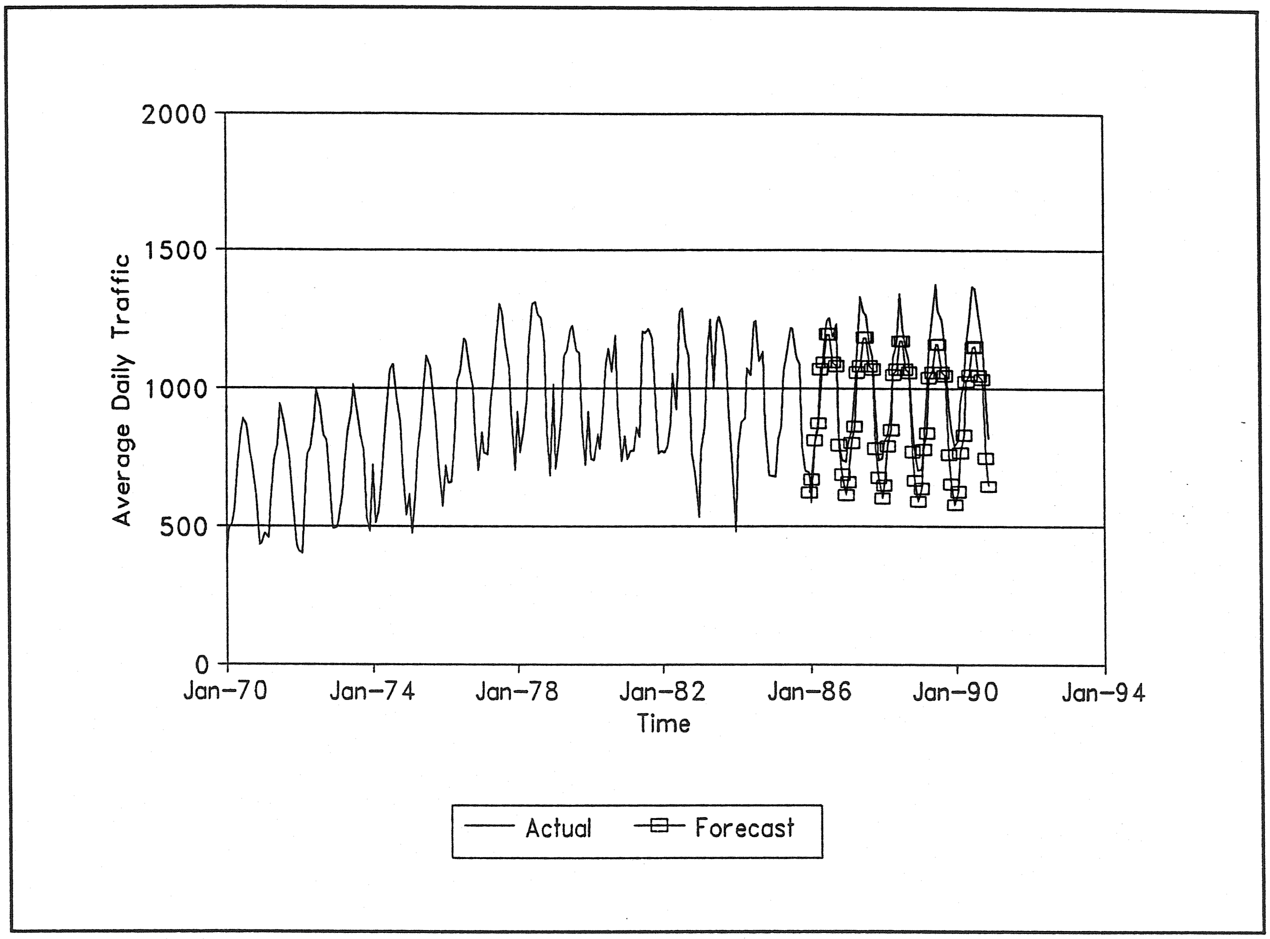

Figure 12. Station 27. St Maries

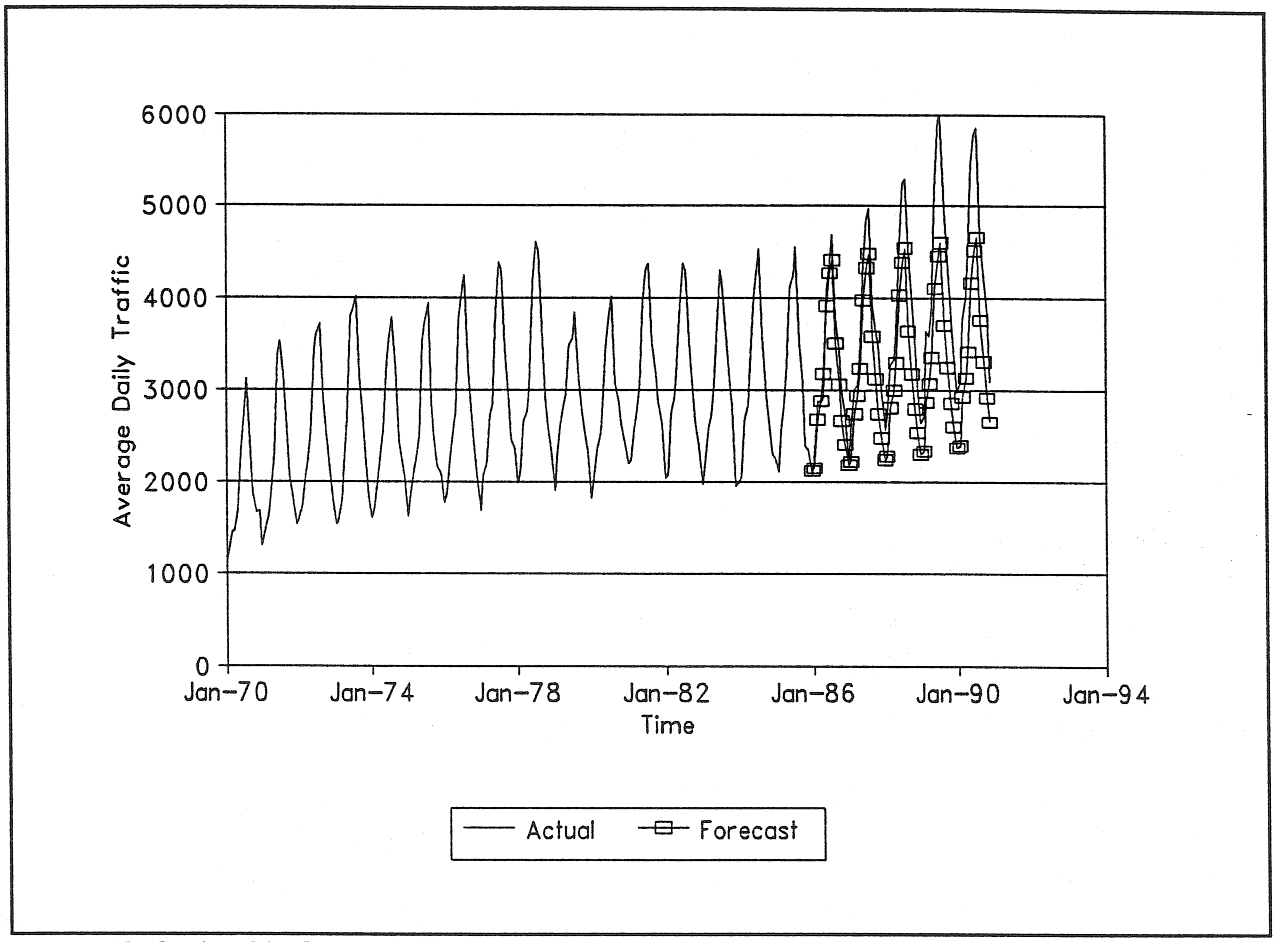

Figure 13. Station 30. Cotterell

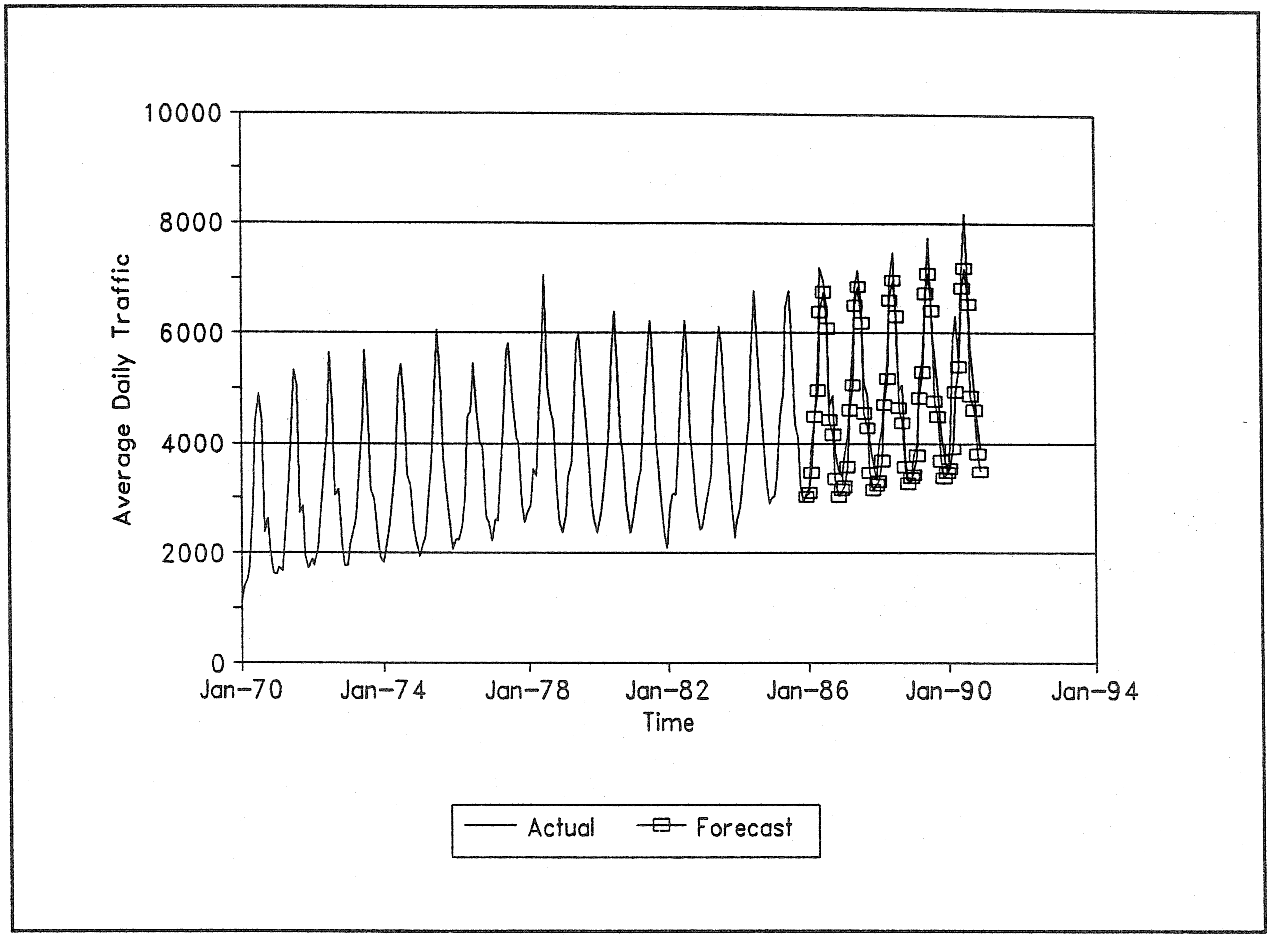

Figure 14. Station 52. Barber Road, Boise

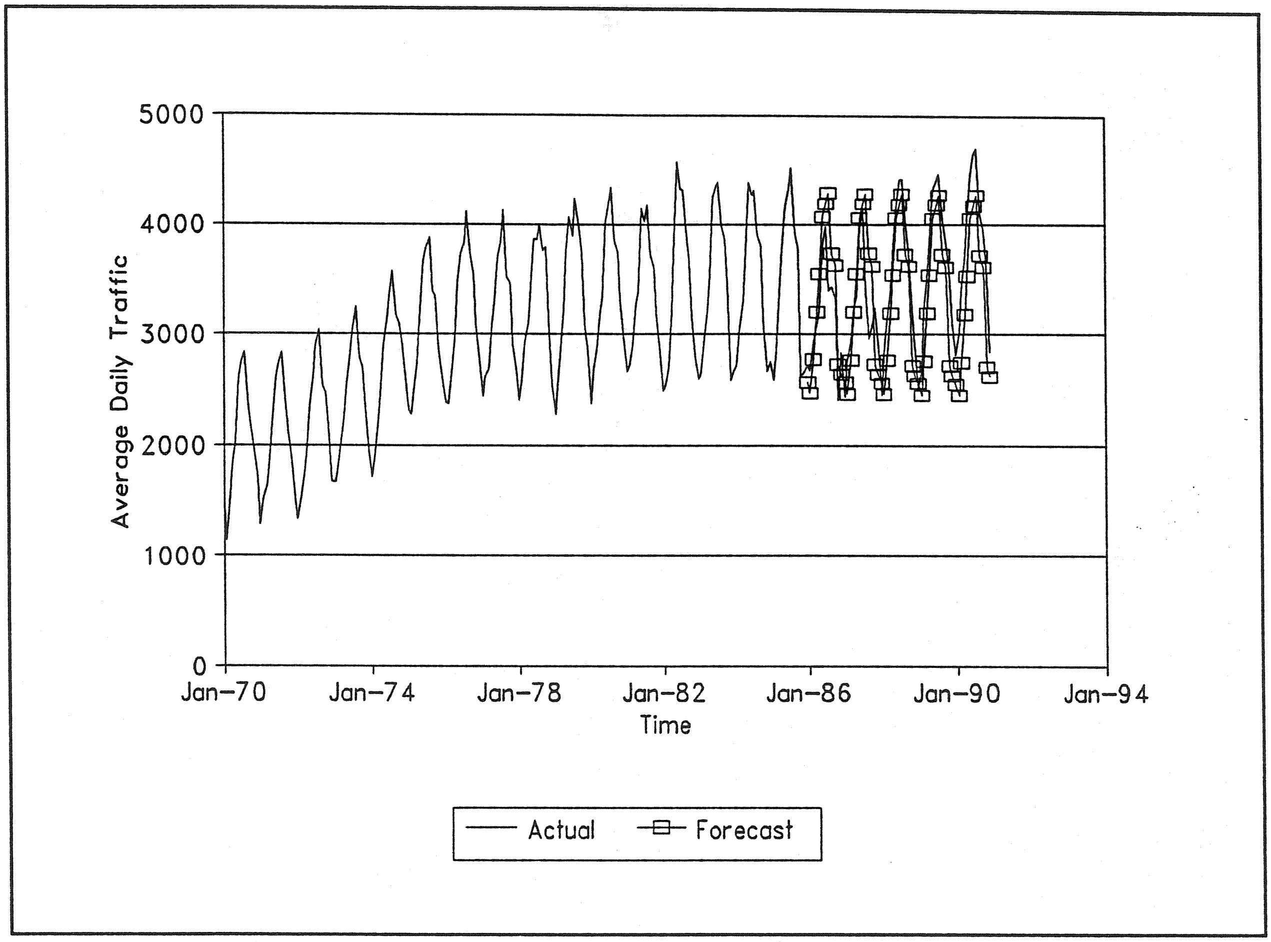

Figure 15. Station 60. Alexandra

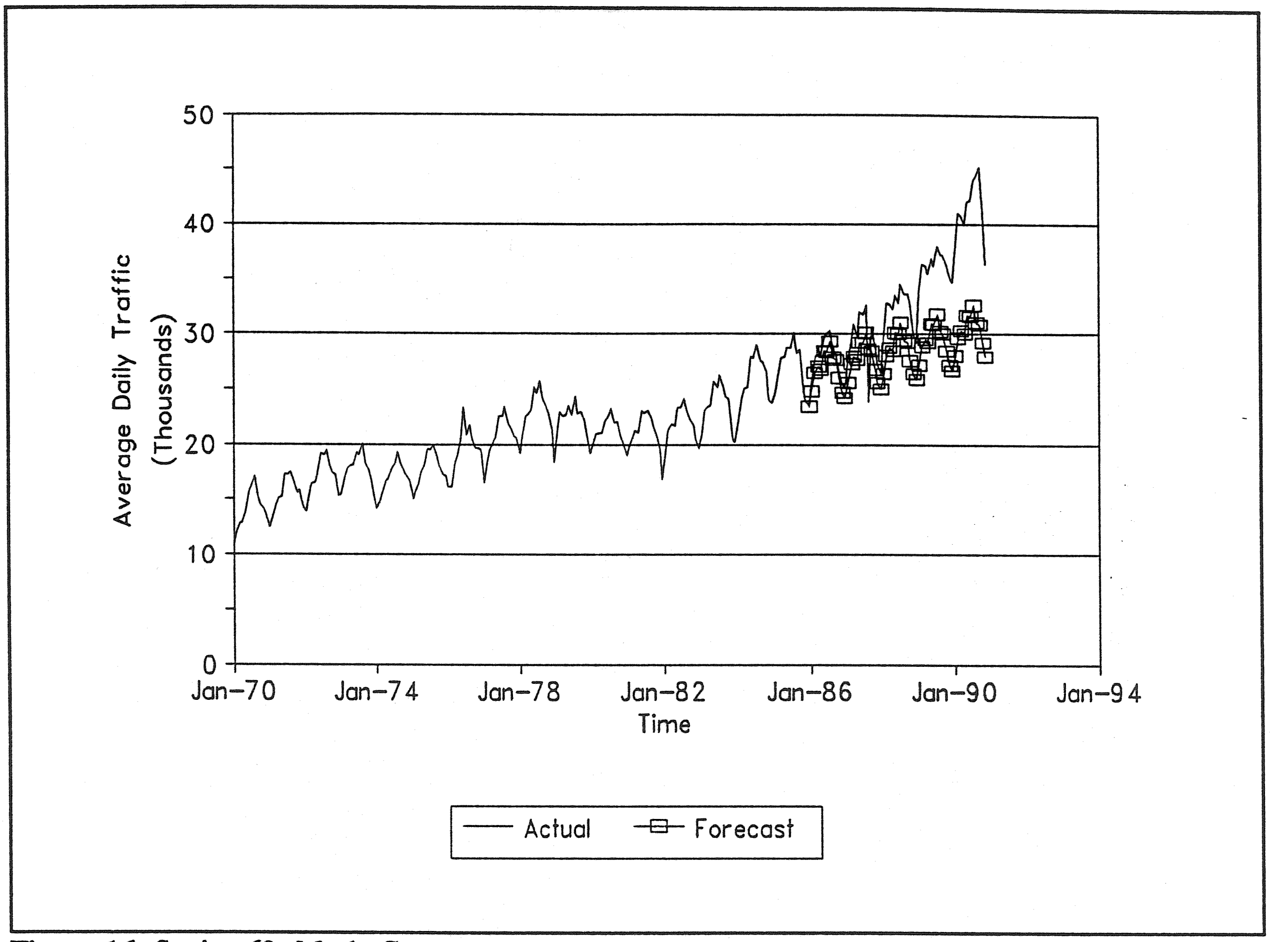

Figure 16. Station 62. Maple Grove

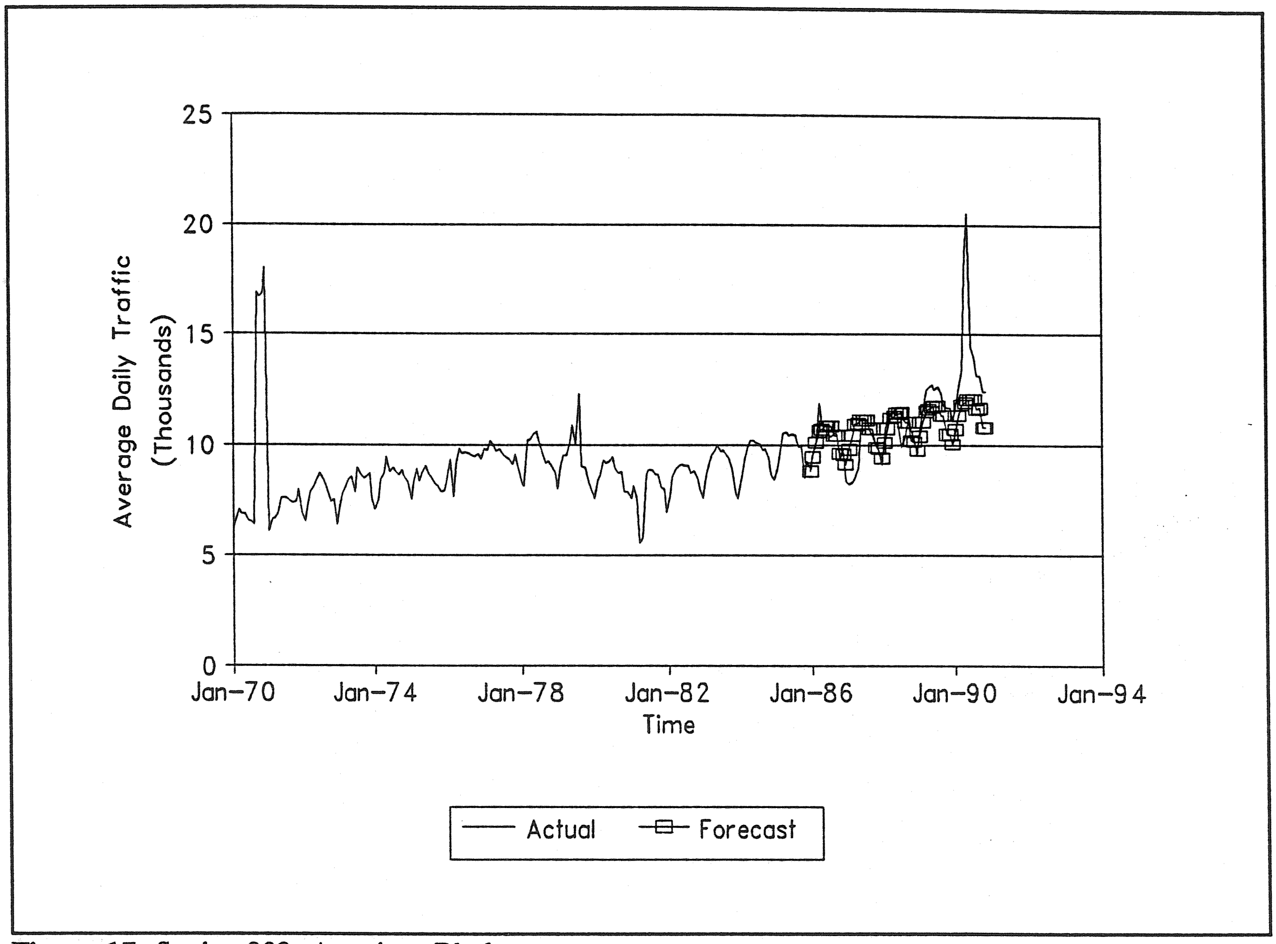

Figure 17. Station 202. American Blvd.

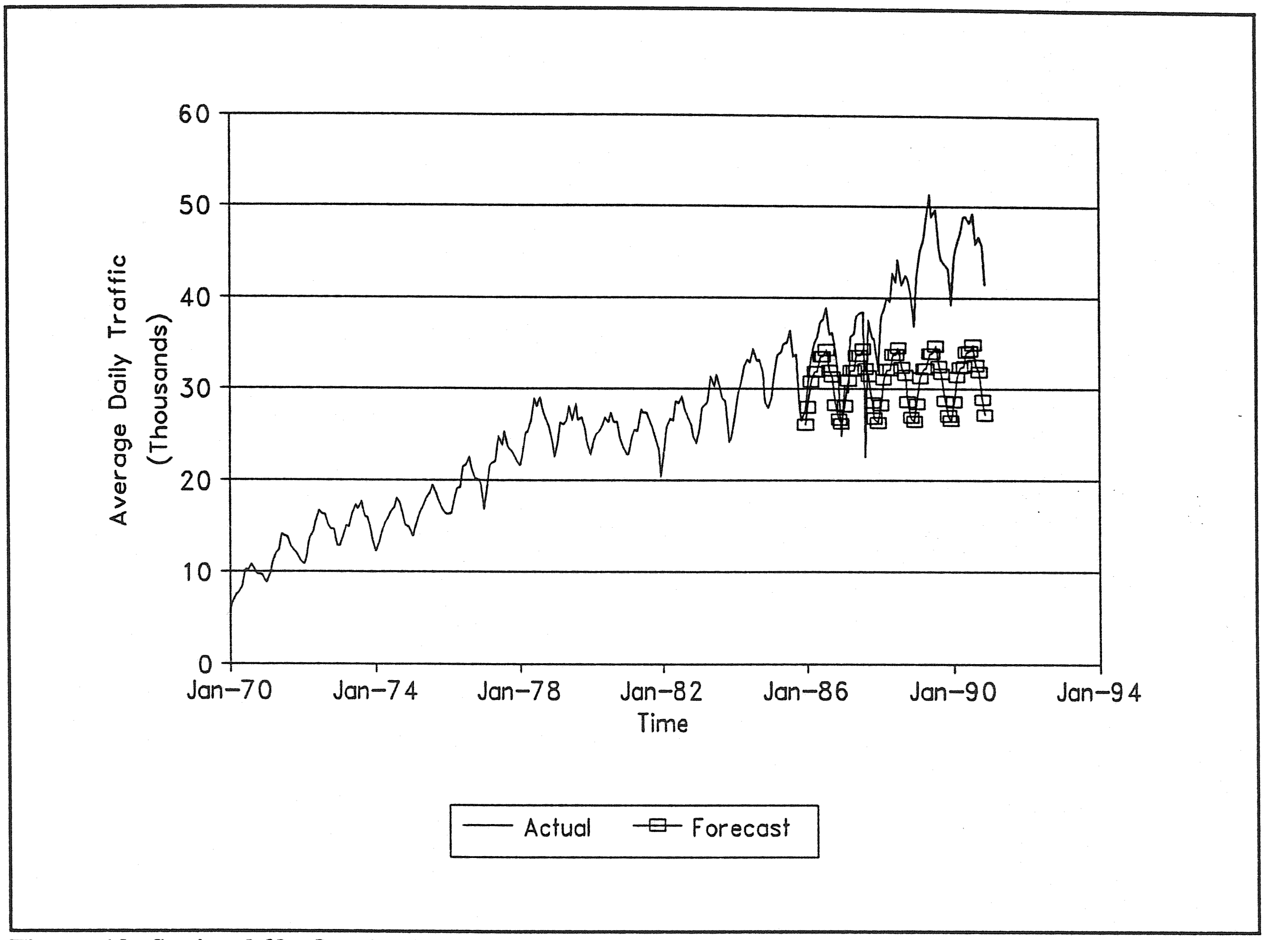

Figure 18. Station 263. Overland Road

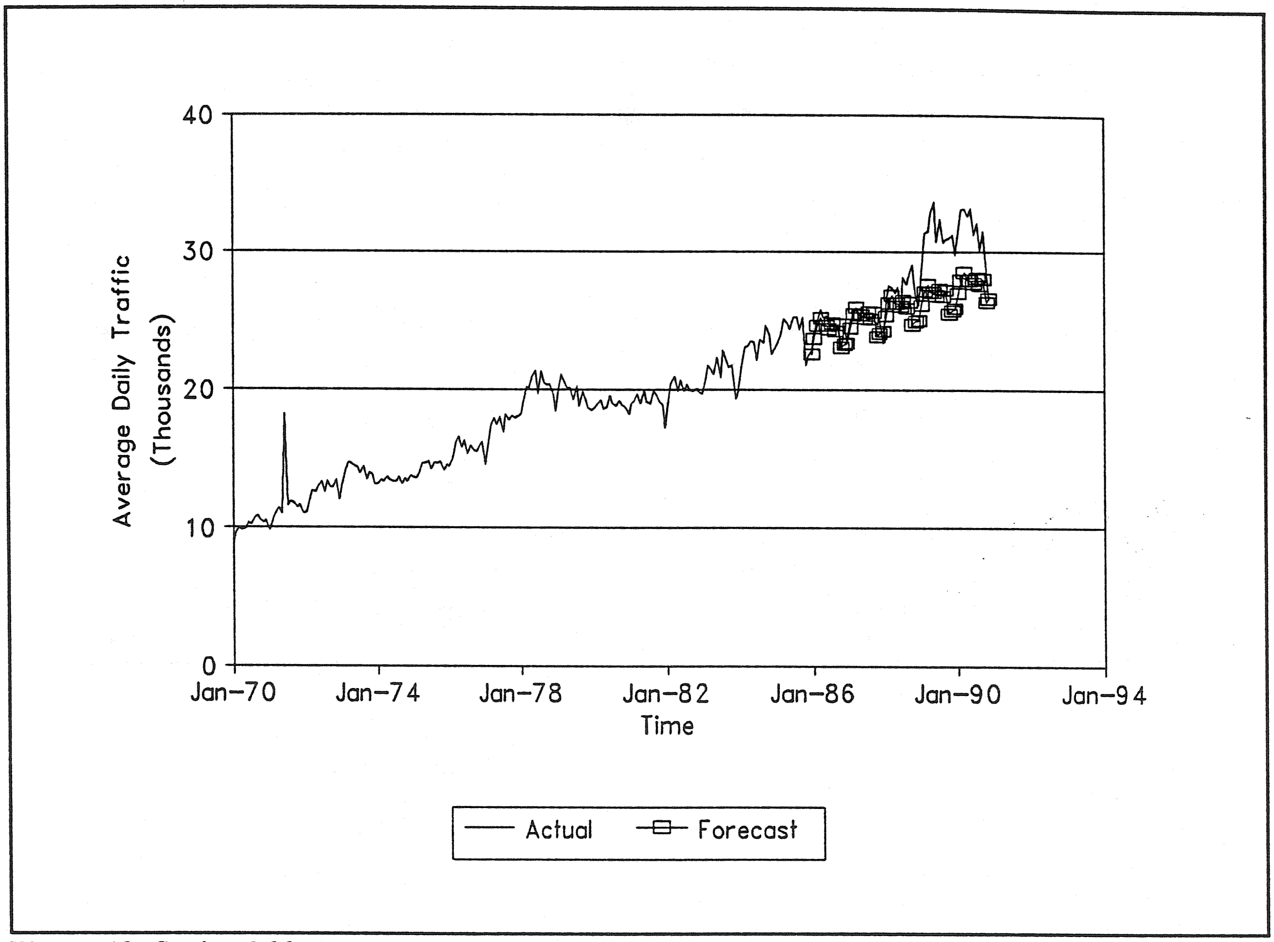

Figure 19. Station 266. Emerald

6.3 Forecasting Average Daily Truck Traffic

Univariate time series models were also prepared for the eleven ATR stations that had at least 48 monthly data points. Forecast were also prepared for a one year ahead period. The results of both the model estimation and the forecasts are given in Table 24. The forecast for each ATR station is given in Figures 20 through 30.

The mean absolute percent error ranges from 2.4 percent to 27.5 percent. The forecast errors are certainly acceptable as compared with other procedures. These are particularly good error ranges since the size of the data set used for estimation and forecasting purposes is relatively small, 48 observations. It can be noted in the figures that the forecasts are able to track the actual measured truck volumes very well.

Table 24. Univariate Truck Model Coefficients and Forecasts

Station	θ_1	θ_{12}	R^2	RSE	MAPE
4	.50	.07	.95	.0067	2.4%
5	.79	.37	.72	.0022	9.4%
7	.12	.25	.86	.0002	5.0%
17	.23	.21	.88	.0031	6.3%
25	.03	.22	.87	.0002	10.3%
27	.27	.38	.83	.0012	7.9%
30	.19	.53	.86	.0001	7.6%
51	-.18	.95	.55	.0004	27.5%
60	.69	.17	.83	.0056	5.5%
71	.08	.25	.83	.0002	14.5%
72	.19	.00	.97	.0063	9.2%

θ_1 and θ_{12} are ARIMA model parameters.
R^2 is the correlation coefficient.
RSE = Residual Standard Error.
MAPE = Mean Absolute Percent Error

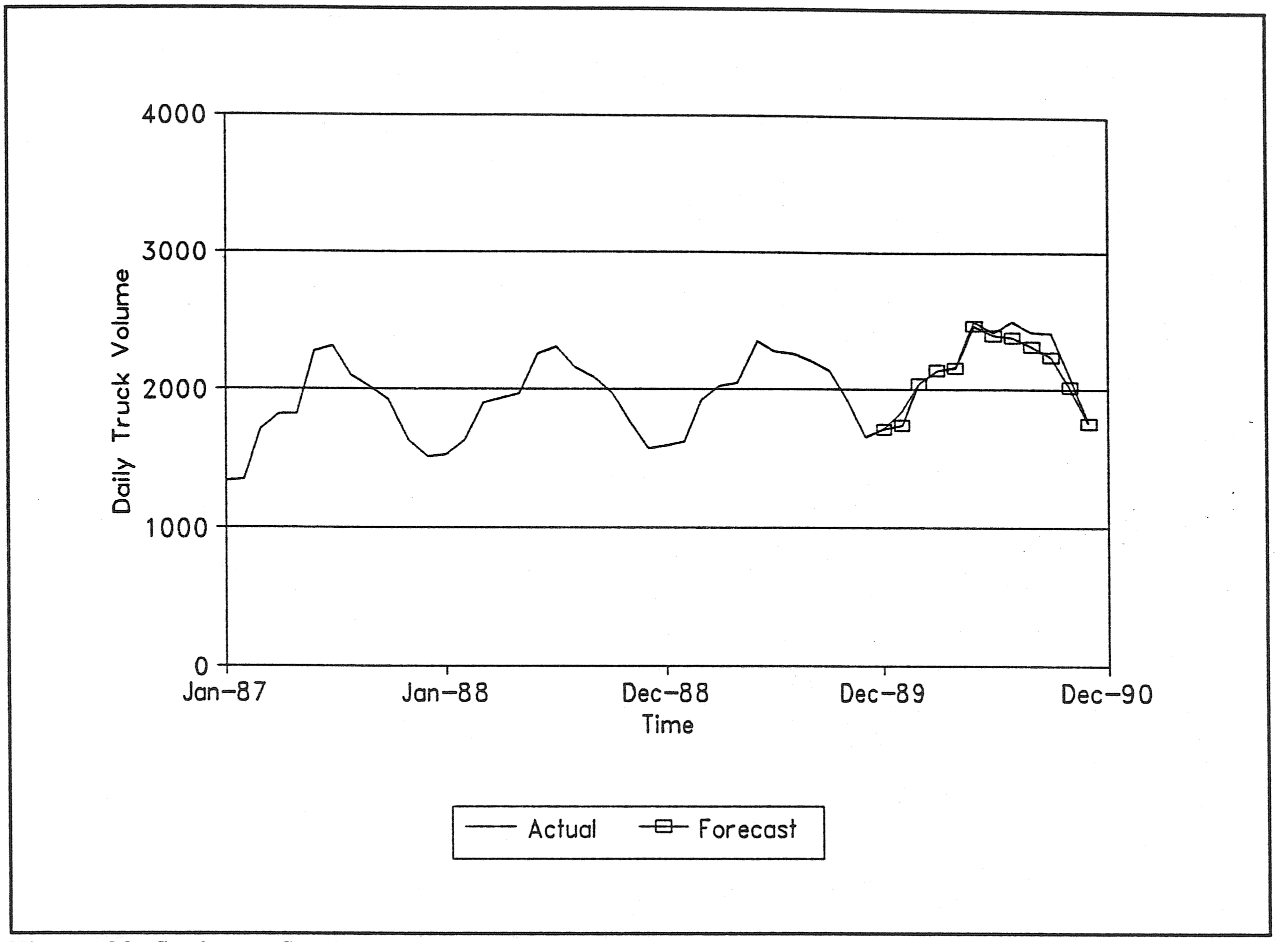

Figure 20. Station 4. South Pocatello

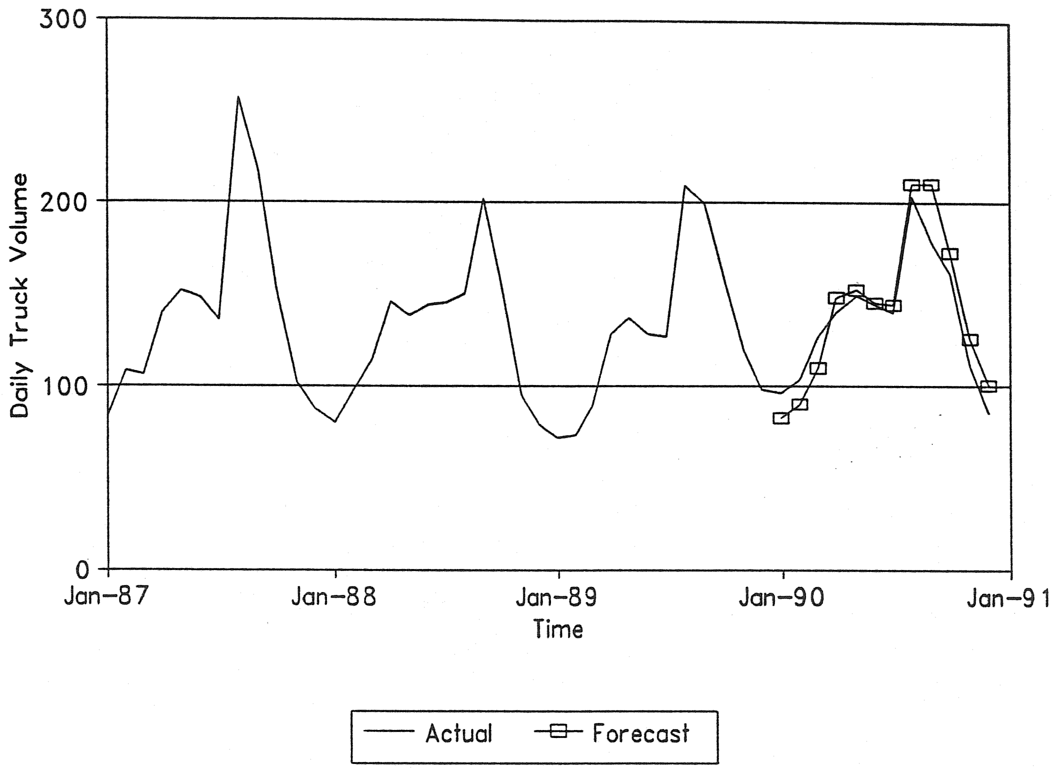

Figure 21. Station 5. North Pocatello

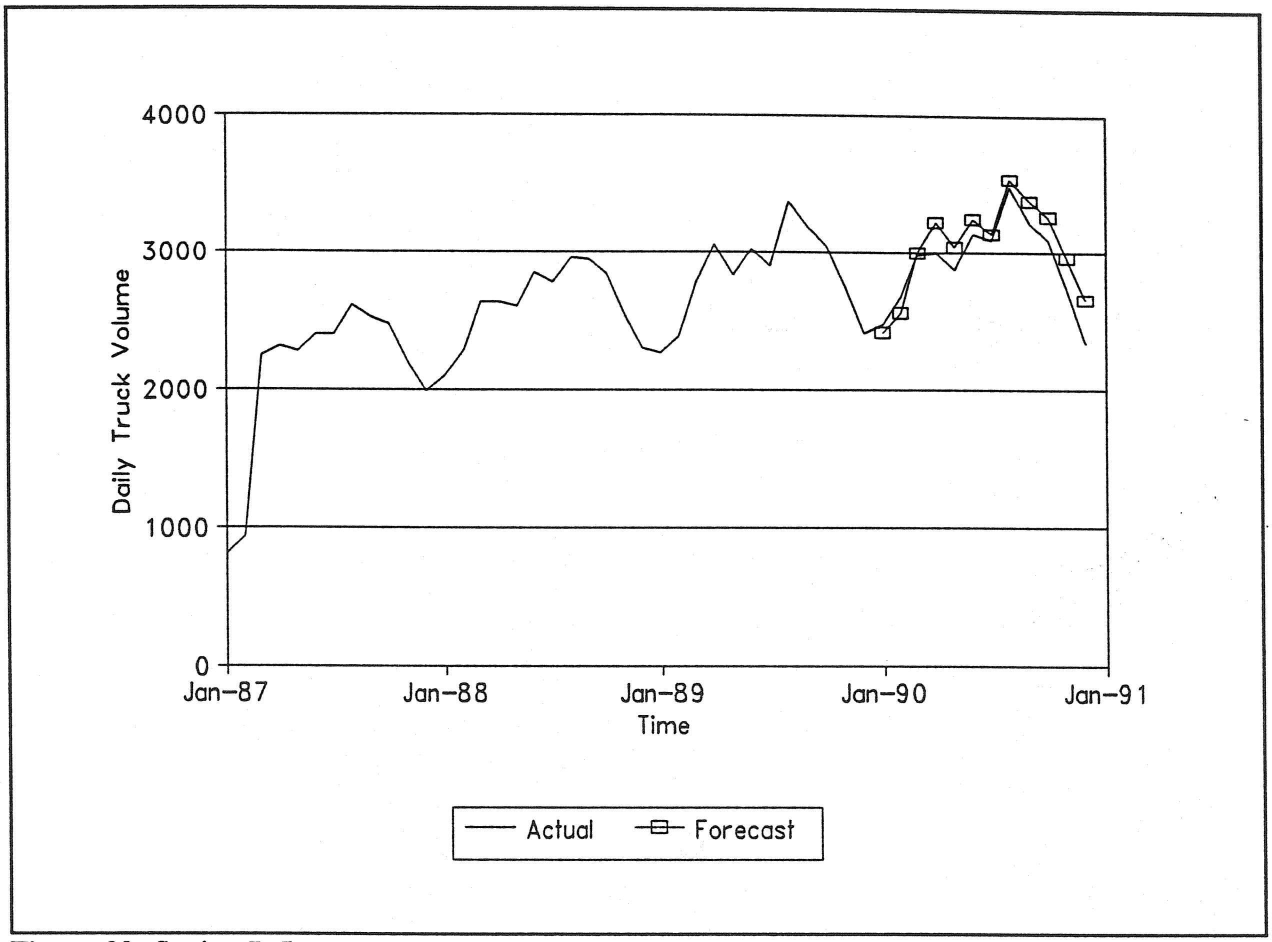

Figure 22. Station 7. Jerome

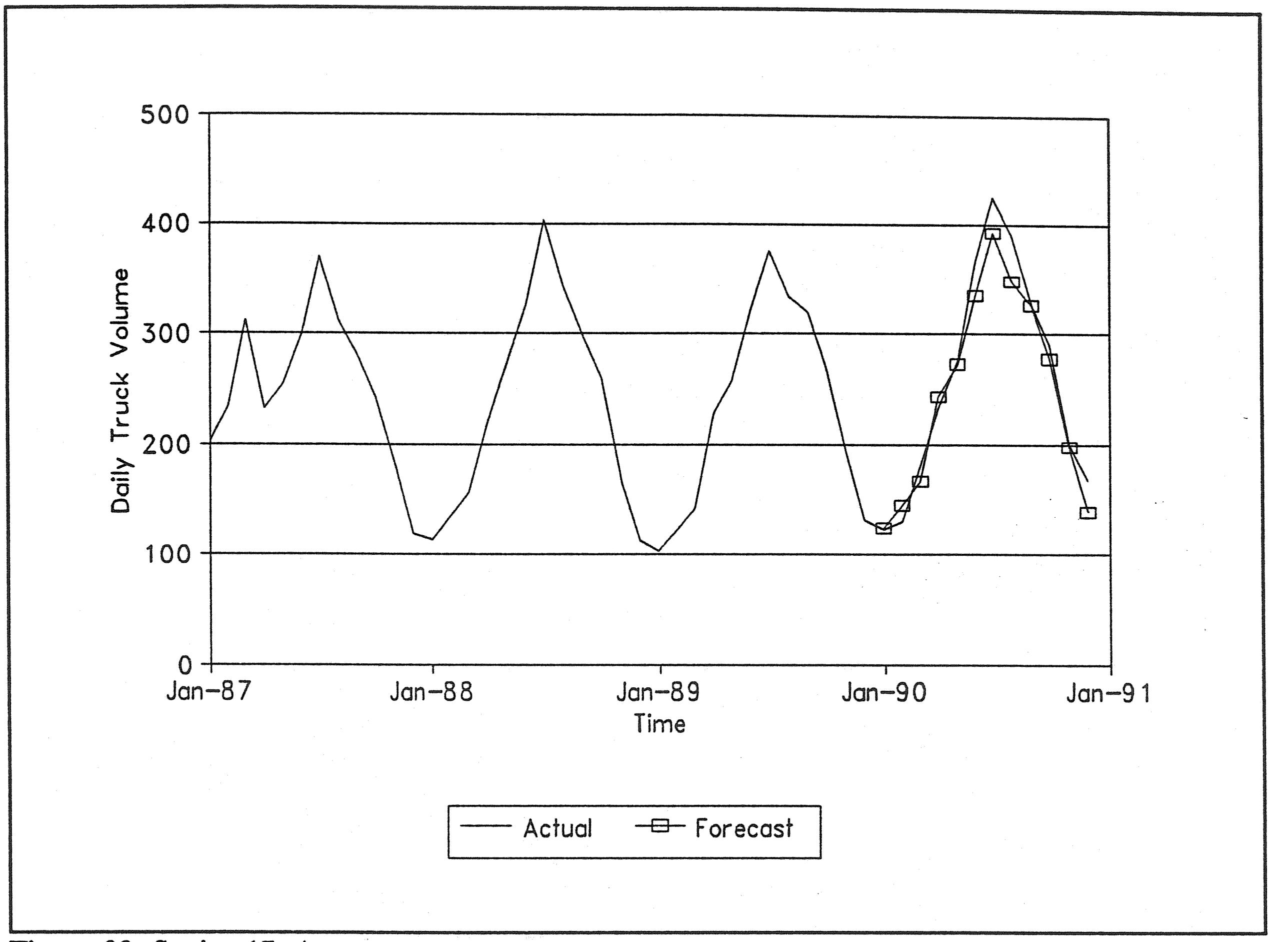

Figure 23. Station 17. Arco

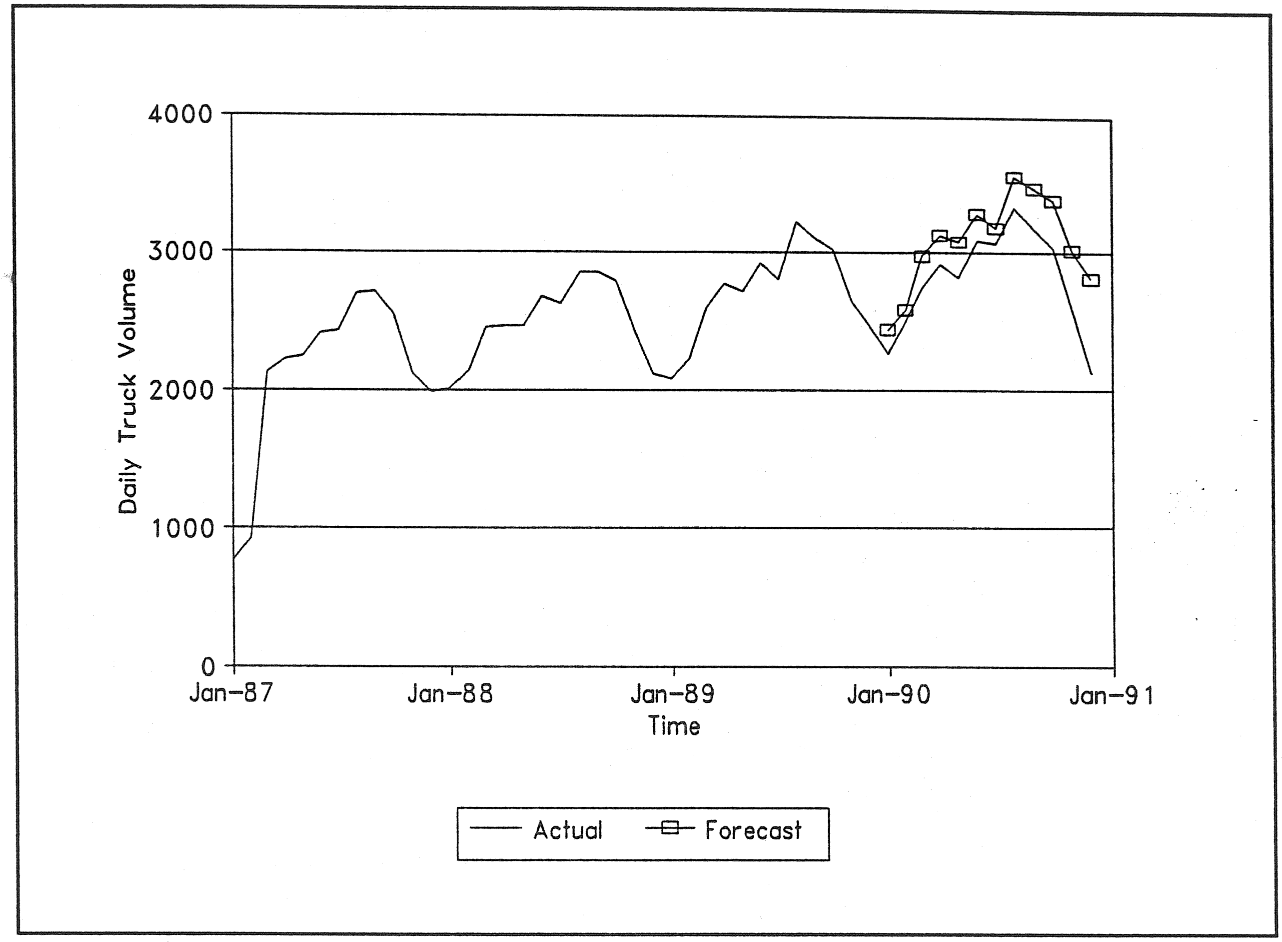

Figure 24. Station 25. Sand Hollow

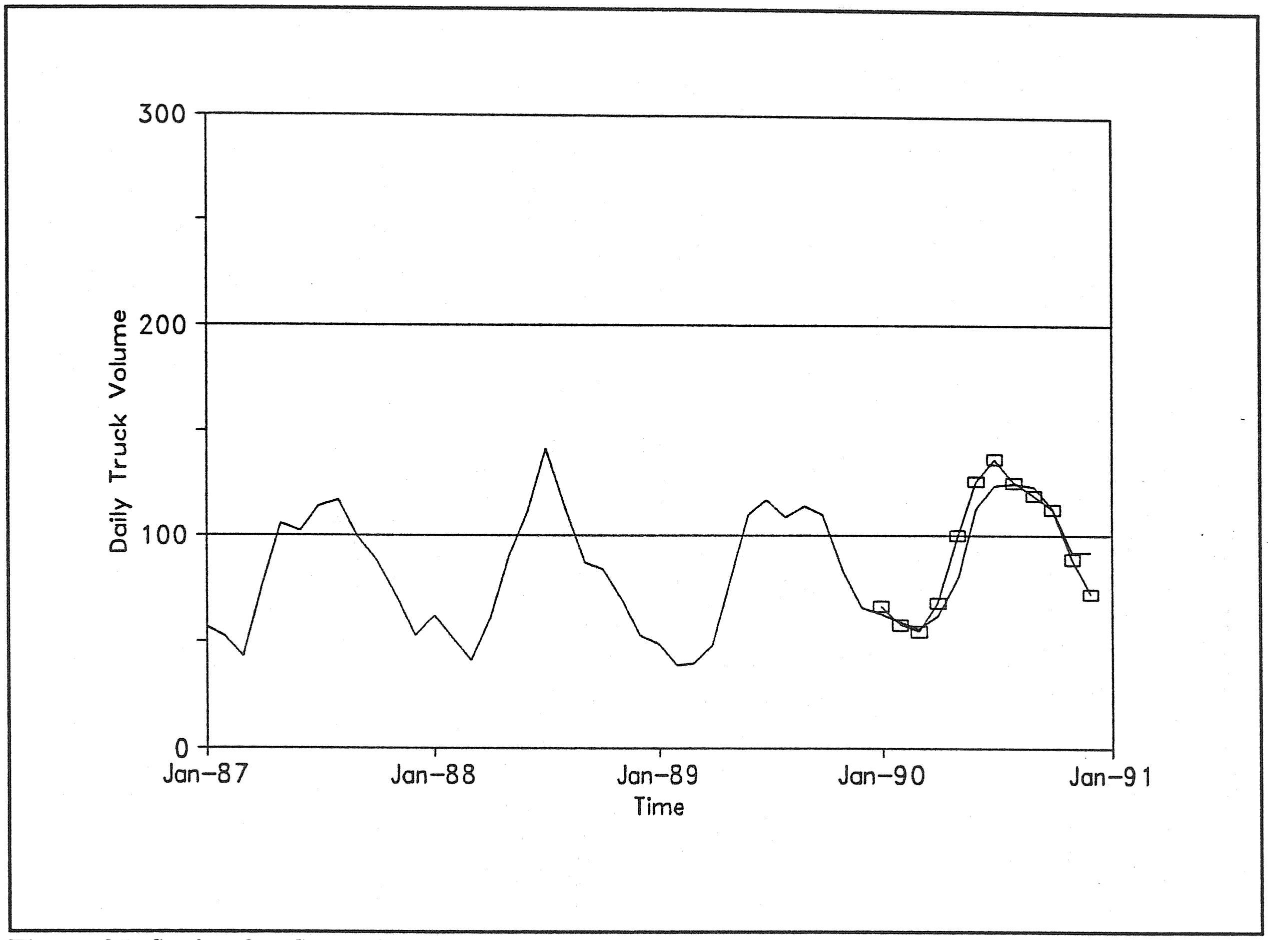

Figure 25. Station 27. St Maries

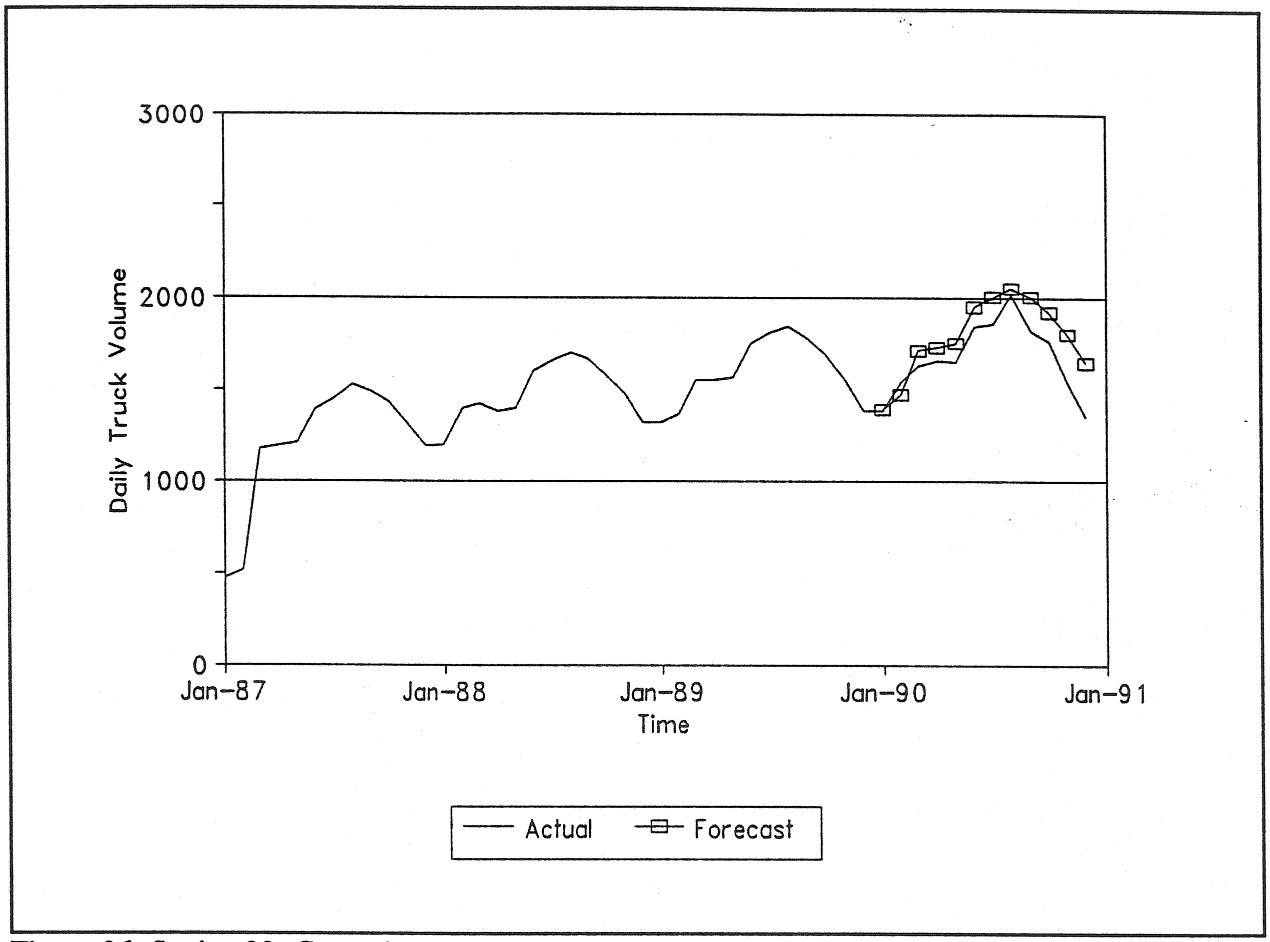

Figure 26. Station 30. Cotteral

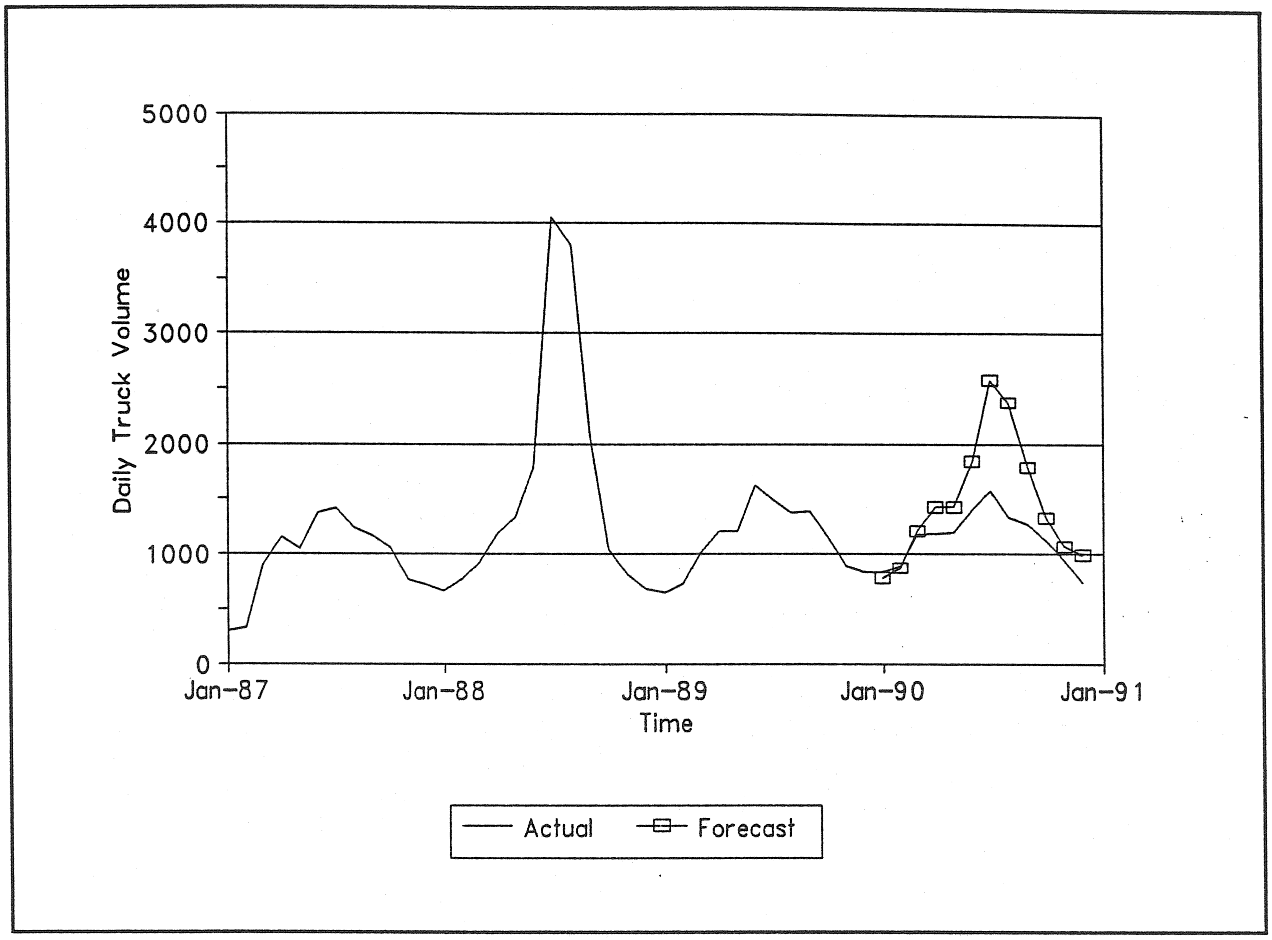

Figure 27. Station 51. Lorenzo

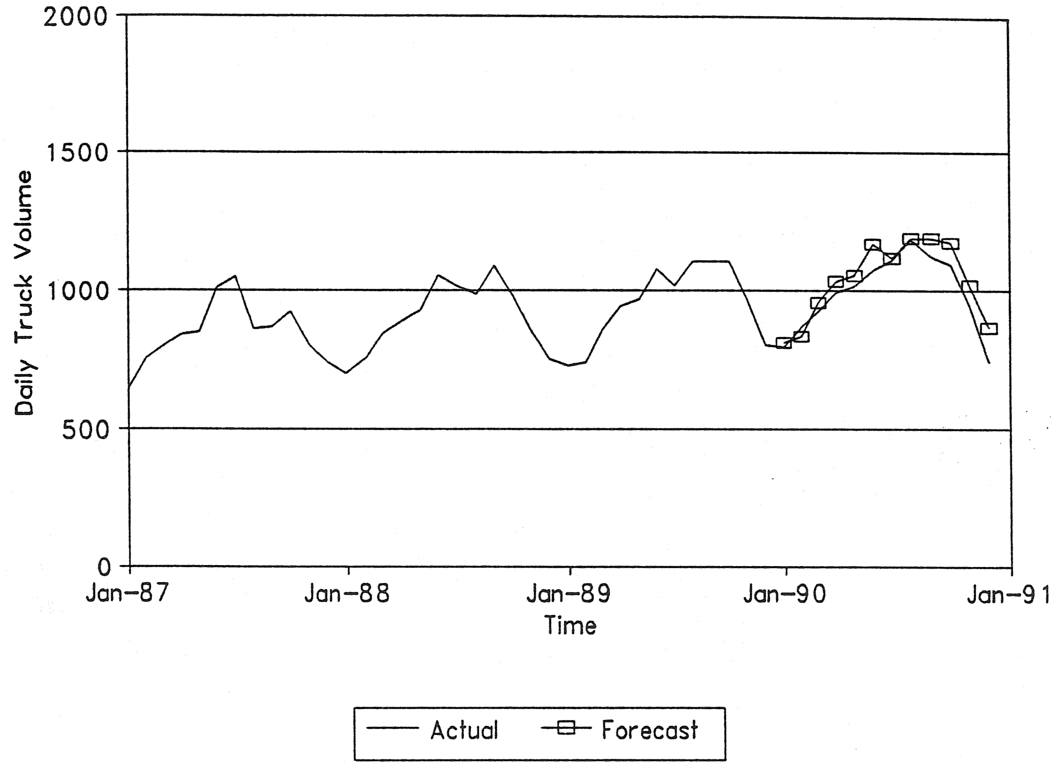

Figure 28. Station 60. Alexandra

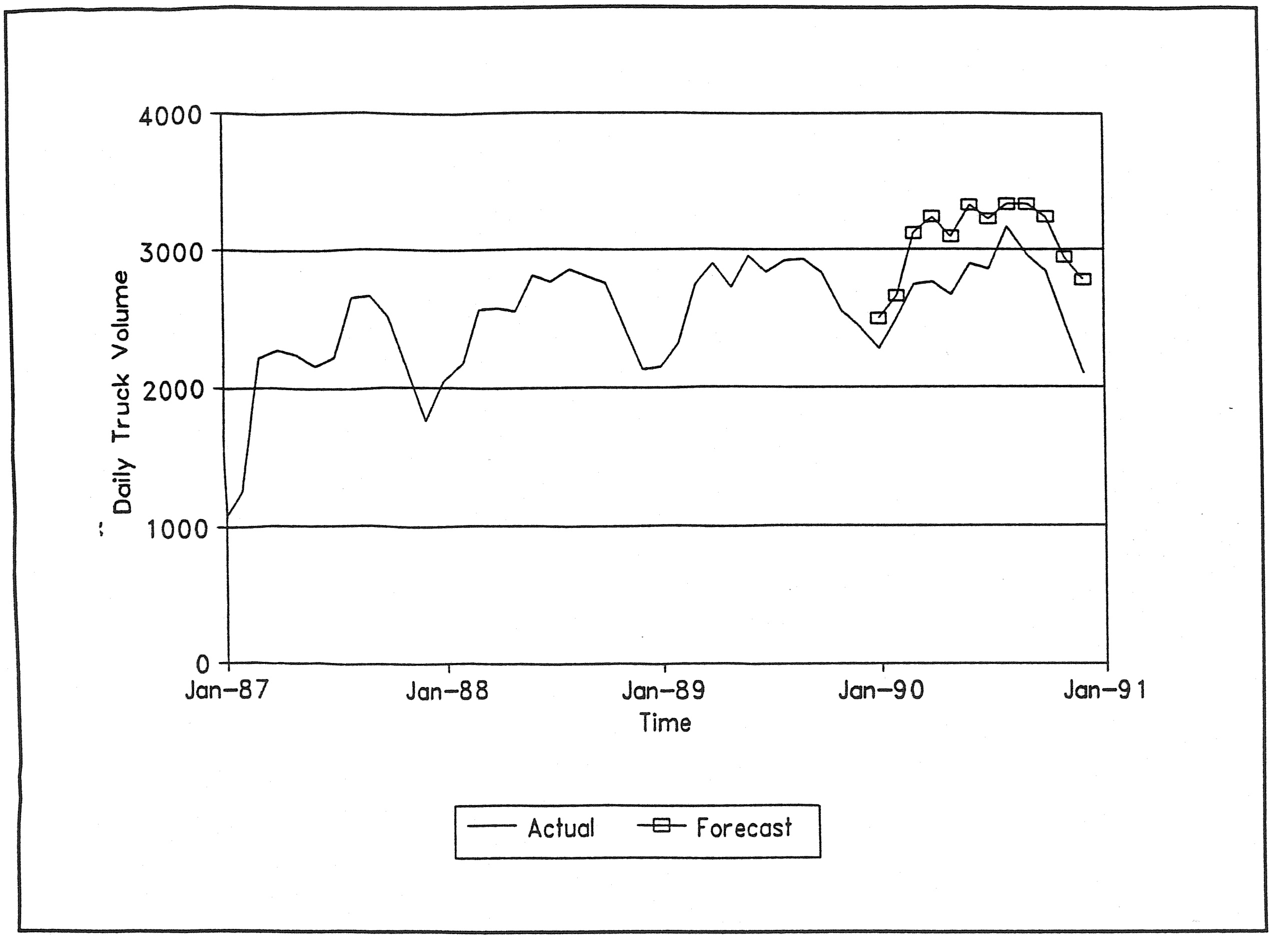

Figure 29. Station 71. Hammett

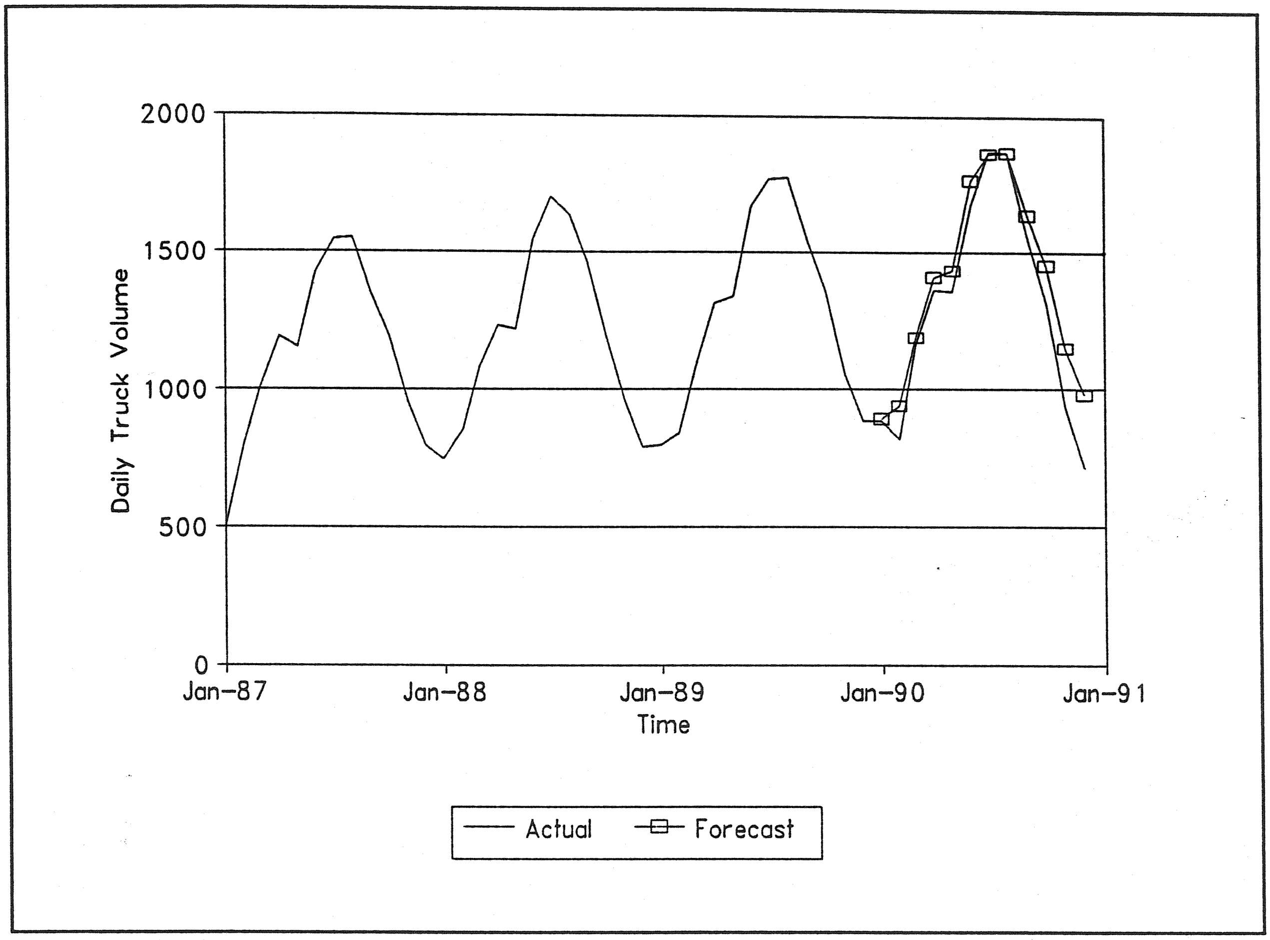

Figure 30. Station 72. Mullan

CHAPTER 7. MULTIVARIATE TIME SERIES MODELS

7.1 Overview

In chapter 6, univariate time series models were estimated and forecasts were prepared for each of the models. In this chapter, the effects of selected variables on traffic volumes are investigated and the improvements to forecasts are compared.

Both univariate and multivariate transfer function models were developed for six interstate highway segments in Ada County. Since the data base for the explanatory variables is much more limited, only 67 monthly data points (representing the time period May 1985 through December 1990) are available. This severely restricts the model development process and probably means that the benefits of the transfer function models cannot be fully realized here. However, the comparative forecasts and the methodology used should be of interest.

7.2 Model Forms

Four models were developed for each of the six stations listed in Table 25, a univariate model and three transfer function models. Each transfer function model included one explanatory variable, gasoline price, employment for Ada County, and the number of vehicle registrations.

Gasoline price was only statistically significant in two of the models. Employment was signficant in all six models, while vehicle registrations was statistically significant in four of the models. Both the model coefficients and the lag period are given in the table. The lag indicates the number of months after a change is measured in which it will have an effect on traffic volumes.

Table 25. Model Parameters

Station	Univariate Model Parameters		Gasoline Price		Employment		Vehicle Registration	
	θ_1	θ_{12}	Lag	Coefficient	Lag	Coefficient	Lag	Coefficient
2	.60	.33	9	-2300.17	9	.1829	1	.2027
62	.73	.84	-	-	0	.3098	-	-
263	.61	.99	-	-	0	.5808	-	-
264	.31	.32	-	-	0	.2313	1	.4130
265	.08	.62	-	-	0	.2095	1	.6746
266	.56	-.53	5	-4065.68	3	.2143	7	.2120

7.3 Model Forecasts

One year ahead forecasts were prepared for each station using the four models listed in Table 25. The results of the forecasts are given in Table 26. The addition of the explanatory variables improved the mean absolute percent forecast error in four of the six models. It should be expected that if a larger data base were available, that the degree of forecast error improvement should be much more significant. Still, this approach does offer some promise and should be considered for use in conjunction with the univariate models for forecasting future traffic volumes.

Table 26. One Year-Ahead Forecasts

Station	Univariate Model	Gasoline Price Model	Employment Model	Vehicle Registration Model
2	5.2%	3.2%	4.7%	5.7%
62	5.8%	-	7.8%	-
263	6.9%	-	6.7%	-
264	4.1%	-	3.9%	3.9%
265	8.4%	-	8.7%	10.2%
266	10.9%	8.5%	6.8%	7.4%

CHAPTER 8. SUMMARY AND CONCLUSIONS

The purpose of this report has been to develop and present a methodology for forecasting future traffic volumes on Idaho highways. This purpose has been accomplished. This chapter presents a brief summary of the major highlights of this effort.

■The forecasting guide developed by Mark Hallenbeck of the Washington Department of Transportation is an excellent general reference guide that should be consulted by ITD staff given the responsibility of both preparing and using traffic forecasts. The guide presents important information for forecasting traffic volumes, truck volumes, and vehicle loadings. The guide does, however, lack specifics reference to one of the most important forecasting techniques that is available, time series analysis.

■Time series analysis methods can be used to forecast future traffic volumes when a good historical data base exists. Such a data base is available to the Idaho Transportation Department through the data generated by the Automatic Traffic Recorder stations located throughout the state of Idaho.

■This report describes the process that can be used to develop time series models using the SAS software system.

■Forecasts prepared for both total traffic and truck traffic using time series models show that this method has considerable merit. Forecast errors are reasonable and compare favorably with other methods.

■It is recommended that the ITD implement the use of this technique on a trial basis.

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Table 1. District 1 Traffic Count Stations

Station	Name	Segment	Milepost	Route	County	Functional Category
26	KOOTENAI	1610	35.98	SH-200	BONNER	RURAL MINOR ARTERIAL
47	PRIEST RIVER	1590	2.64	US-2	BONNER	RURAL PRINCIPAL ARTERIAL
16	BONNERS FERRY	1540	509.36	US-95	BOUNDARY	RURAL PRINCIPAL ARTERIAL
46	COPELAND	1540	527.28	US-95	BOUNDARY	RURAL PRINCIPAL ARTERIAL
1	POST FALLS	1660	6.16	I-90	KOOTENAI	URBAN P.A. INTERSTATE
8	DUDLEY	1660	35.59	I-90	KOOTENAI	RURAL INTERSTATE
21	CHILCO	1540	442.74	US-95	KOOTENAI	RURAL PRINCIPAL ARTERIAL
27	ST MARIES	1600	95.34	SH-3	KOOTENAI	RURAL MINOR ARTERIAL
40	RATHOROM	1650	6.64	SH-53	KOOTENAI	RURAL MINOR ARTERIAL
41	N. RATHORUM	1630	8.96	SH-41	KOOTENAI	RURAL MAJOR COLLECTOR
42	ATHOL	1640	8.36	SH-54	KOOTENAI	RURAL MAJOR COLLECTOR
72	MULLAN	1660	69.31	I-90	SHOSHONE	RURAL INTERSTATE

Table 2. District 2

Station	Name	Segment	Milepost	Route	County	Functional Category
39	FENN	1540	247.03	US-95	IDAHO	RURAL PRINCIPAL ARTERIAL
49	RIGGINS	1540	203.7	US-95	IDAHO	RURAL PRINCIPAL ARTERIAL
84	POWELL	1910	163.01	US-12	IDAHO	RURAL PRINCIPAL ARTERIAL
85	LOWELL	1910	97.9	US-12	IDAHO	RURAL PRINCIPAL ARTERIAL
15	POTLATCH	1540	363.69	US-95	LATAH	RURAL PRINCIPAL ARTERIAL
45	BOVILL	1800	39.89	SH-3	LATAH	RURAL MINOR ARTERIAL
19	KAMIAH	1910	63.663	US-12	LEWIS	RURAL PRINCIPAL ARTERIAL
6	LEWISTON	1540	305.1	US-95	NEZ PERCE	RURAL PRINCIPAL ARTERIAL

Table 3. District 3 Traffic Count Stations

Station	Name	Segment	Milepost	Route	County	Functional Category
2	JEANS PLACE	1010	58.73	I-84	ADA	RURAL INTERSTATE
10	DRY CREEK	1990	47.83	SH-55	ADA	RURAL PRINCIPAL ARTERIAL
52	BARBER RD. BOISE	2140	5.62	SH-21	ADA	URBAN MINOR ARTERIAL
62	MAPLE GROVE BOISE	1010	48.93	I-84	ADA	URBAN P.A. INTERSTATE
80	ECKERT ROAD BOISE	2140	4.144	SH-21	ADA	URBAN MINOR ARTERIAL
200	STATE ST. BOISE	2130	29.9	FAU 7063	ADA	URBAN PRINCIPAL ARTERIAL
202	AMERICANA BOISE	2320	1.665	FAU 7363	ADA	URBAN PRINCIPAL ARTERIAL
209	FAIRVIEW AVENUE BOISE	2070	47.58	US-20	ADA	URBAN MINOR ARTERIAL
210	MAIN STREET BOISE	2071	47.37	US-30	ADA	URBAN MINOR ARTERIAL
211	WARM SPRINGS BOISE	2700	1.3	FAU 7383	ADA	URBAN MINOR ARTERIAL
212	CAPITOL BLVD. BOISE	2670	49.33	FAU 7553	ADA	URBAN PRINCIPAL ARTERIAL
213	BROADWAY AVENUE BOISE	2070	49.9	US-20	ADA	URBAN PRINCIPAL ARTERIAL
216	9TH STREET BOISE	2920	1	FAU 7553	ADA	URBAN PRINCIPAL ARTERIAL
217	GLENWOOD AVENUE BOISE	2850	0.77	SH-44	ADA	URBAN PRINCIPAL ARTERIAL
218	VETERANS BOISE	2753	2.5	FAU 7113	ADA	URBAN MINOR ARTERIAL
263	OVERLAND IC BOISE	1010	49.71	I-84	ADA	URBAN P.A. INTERSTATE

Table 4. District 3 Traffic Count Stations

Station	Name	Segment	Milepost	Route	County	Functional Category
264	VISTA IC BOISE	1010	53.08	I-84	ADA	URBAN P.A. INTERSTATE
265	BROADWAY IC BOISE	1010	53.92	I-84	ADA	URBAN P.A. INTERSTATE
266	EMERALD BOISE	2410	1.78	I-164	ADA	URBAN P.A. INTERSTATE
270	EAGLE ROAD	2005	17.74	SH-55	ADA	RURAL PRINCIPAL ARTERIAL
272	STAR ROAD	2560	9.98	FAS 3770	ADA	RURAL MAJOR COLLECTOR
273	BOGUS BASIN BOISE	2133	1.104	FAU 7363	ADA	URBAN MINOR ARTERIAL
23	COUNCIL	1540	140.38	US-95	ADAMS	RURAL PRINCIPAL ARTERIAL

Table 5. District 3

53	ROBIE CREEK	2140	20.59	SH-21	BOISE	RURAL MINOR ARTERIAL
81	GRANDJEAN	2140	93.9	SH-21	BOISE	RURAL MINOR ARTERIAL
83	GARDEN VALLEY	3770	9.27	FAS 3824	BOISE	RURAL MAJOR COLLECTOR
86	BANNER SUMMIT	2140	105.3	SH-21	BOISE	RURAL MINOR ARTERIAL
9	CALDWELL	2050	15.76	SH-19	CANYON	RURAL MAJOR COLLECTOR
25	SAND HOLLOW	1010	19.1	I-84	CANYON	RURAL INTERSTATE
203	16TH AVENUE NAMPA	4340	0.12	FAU 8353	CANYON	URBAN MINOR ARTERIAL
205	10TH AVENUE CALDWELL	2040	49.8	FAU 7773	CANYON	URBAN PRINCIPAL ARTERIAL

Table 6. District 3

Station	Name	Segment	Milepost	Route	County	Functional Category
220	AMITY ROAD NAMPA	2600	0.04	FAU 8423	CANYON	URBAN MINOR ARTERIAL
221	NAMPA BLVD. NAMPA	1990	18.5	SH-55	CANYON	URBAN PRINCIPAL ARTERIAL
222	KARCHER ROAD NAMPA	4760	0.31	FAU 8223	CANYON	URBAN COLLECTOR
223	MIDDLETON ROAD NAMPA	4700	0.28	FAU 8213	CANYON	URBAN MINOR ARTERIAL
224	OSTICK ROAD CALDWELL	4875	5.13	FAU 7923	CANYON	URBAN MINOR ARTERIAL
225	LINDEN ROAD CALDWELL	4530	9.04	FAU 7923	CANYON	URBAN MINOR ARTERIAL
226	21ST AVENUE CALDWELL	4650	0.23	FAU 7933	CANYON	URBAN MINOR ARTERIAL
227	CENTENNIAL CALDWELL	4635	0.218	I-84 BUS	CANYON	URBAN PRINCIPAL ARTERIAL
54	MOUNTAIN HOME	2070	102.02	US-20	ELMORE	RURAL PRINCIPAL ARTERIAL
71	HAMMETT	1010	114.5	I-84	ELMORE	RURAL INTERSTATE
38	MARSING	1540	22.72	US-95	OWYHEE	RURAL PRINCIPAL ARTERIAL
123	BLACK CANYON	1010	14.9	I-84	PAYETTE	RURAL INTERSTATE
43	DONNELLY	1990	127.72	SH-55	VALLEY	RURAL PRINCIPAL ARTERIAL
44	WEISER	1540	77.96	US-95	WASHINGTON	RURAL PRINCIPAL ARTERIAL

Table 7. District 4

Station	Name	Segment	Milepost	Route	County	Functional Category
68	HAILEY	2230	119.4	SH-75	BALINE	RURAL MINOR ARTERIAL
28	KETCHUM	2230	136.16	SH-75	BLAINE	RURAL MINOR ARTERIAL
18	RAFT RIVER	1260	14.41	I-86	CASSIA	RURAL INTERSTATE
30	COTTERAL	1010	228.68	I-84	CASSIA	RURAL INTERSTATE
7	JEROME	1010	159.23	I-84	GOODING	RURAL INTERSTATE
14	SHOSHONE	2230	79.67	SH-75	LINCOLN	RURAL MINOR ARTERIAL
3	TWIN FALLS	2040	220.69	US-30	TWIN FALLS	RURAL MAJOR COLLECTOR
29	ROGERSON	2220	17.28	US-93	TWIN FALLS	RURAL PRINCIPAL ARTERIAL

Table 8. District 5

Station	Name	Segment	Milepost	Route	County	Functional Category
4	S. POCATELLO	1330	61.87	I-15	BANNOCK	RURAL INTERSTATE
5	N. POCATELLO	2350	83.77	US-91	BANNOCK	RURAL MAJOR COLLECTOR
24	CUBBUCK	1330	72.78	I-15	BANNOCK	URBAN P.A. INTERSTATE
248	HAWTHORNNE CHUBBOCK	1260	60.7	I-86	BANNOCK	URBAN P.A. INTERSTATE
249	CHUBBOCK ROAD CUBBOCK	3160	1.47	FAU 7041	BANNOCK	URBAN MINOR ARTERIAL
250	QUINN ROAD POCATELLO	2350	78.076	US-91	BANNOCK	URBAN PRINCIPAL ARTERIAL
251	ALAMEDA ROAD POCATELLO	3190	1.158	FAU 7101	BANNOCK	URBAN MINOR ARTERIAL
252	CEDAR STREET POCATELLO	4584	0.911	FAU 7361	BANNOCK	URBAN COLLECTOR
253	MAPLE STREET POCATELLO	3200	0.96	FAU 7141	BANNOCK	URBAN COLLECTOR
254	GOULD STREET POCATELLO	2046	0.097	FAU 7181	BANNOCK	URBAN PRINCIPAL ARTERIAL
255	CENTER STREET POCATELLO	3270	299.118	FAU 7341	BANNOCK	URBAN PRINCIPAL ARTERIAL
256	BENTON STREET POCATELLO	2044	2.595	FAU 7151	BANNOCK	URBAN PRINCIPAL ARTERIAL
257	CHEYENNE POCATELLO	3290	3.595	FAU 7271	BANNOCK	URBAN COLLECTOR
11	PARIS	2380	13.83	US-89	BEAR LAKE	RURAL MINOR ARTERIAL
34	GENEVA	2380	38.51	US-89	BEAR LAKE	RURAL MINOR ARTERIAL
36	BORDER	2040	446.5	US-30	BEAR LAKE	RURAL PRINCIPAL ARTERIAL
60	ALEXANDER	2040	399.2	US-30	CARIBOU	RURAL PRINCIPAL ARTERIAL
35	BANIOA	2390	19.69	US-91	FRANKLIN	RURAL MINOR ARTERIAL
22	MALAD	1330	1.3	I-15	OWEIGA	RURAL INTERSTATE
67	POCATELLO AIRPORT	1260	56.4	I-86	POWER	RURAL INTERSTATE

Table 9. District 6 Traffic Count Stations

Station	Name	Segment	Milepost	Route	County	Functional Category
12	RIRIE	2240	352.82	US-26	BONNEVILLE	RURAL PRINCIPAL ARTERIAL
31	SWAN VALLEY	2450	3.54	SH-31	BONNEVILLE	RURAL MAJOR COLLECTOR
57	KETTLE BUTTE	2070	295.02	US-20	BONNEVILLE	RURAL PRINCIPAL ARTERIAL
17	ARCO	2240	252.38	US-20	BUTTE	RURAL PRINCIPAL ARTERIAL
50	CRATERS	2240	229.51	US-93	BUTTE	RURAL PRINCIPAL ARTERIAL
56	HOWE	2460	21.94	US-33	BUTTE	RURAL MAJOR COLLECTOR
55	DICKEY	2220	124.06	US-93	CUSTER	RURAL PRINCIPAL ARTERIAL
82	CLAYTON	2230	227	SH-75	CUSTER	RURAL MINOR ARTERIAL
32	ASHION	2070	377.08	US-20	FREEMONT	RURAL PRINCIPAL ARTERIAL
51	LORENZO	2070	325.74	US-20	JEFFERSON	RURAL PRINCIPAL ARTERIAL
61	ROBERTS	1330	132.78	I-15	JEFFERSON	RURAL INTERSTATE
13	SALMON	2220	301.57	US-93	LEHHI	RURAL PRINCIPAL ARTERIAL
58	LEADORE	2500	89.96	SH-28	LEMHI	RURAL MINOR ARTERIAL
59	NEWDALE	2460	110.1	SH-33	MADISON	RURAL MAJOR COLLECTOR

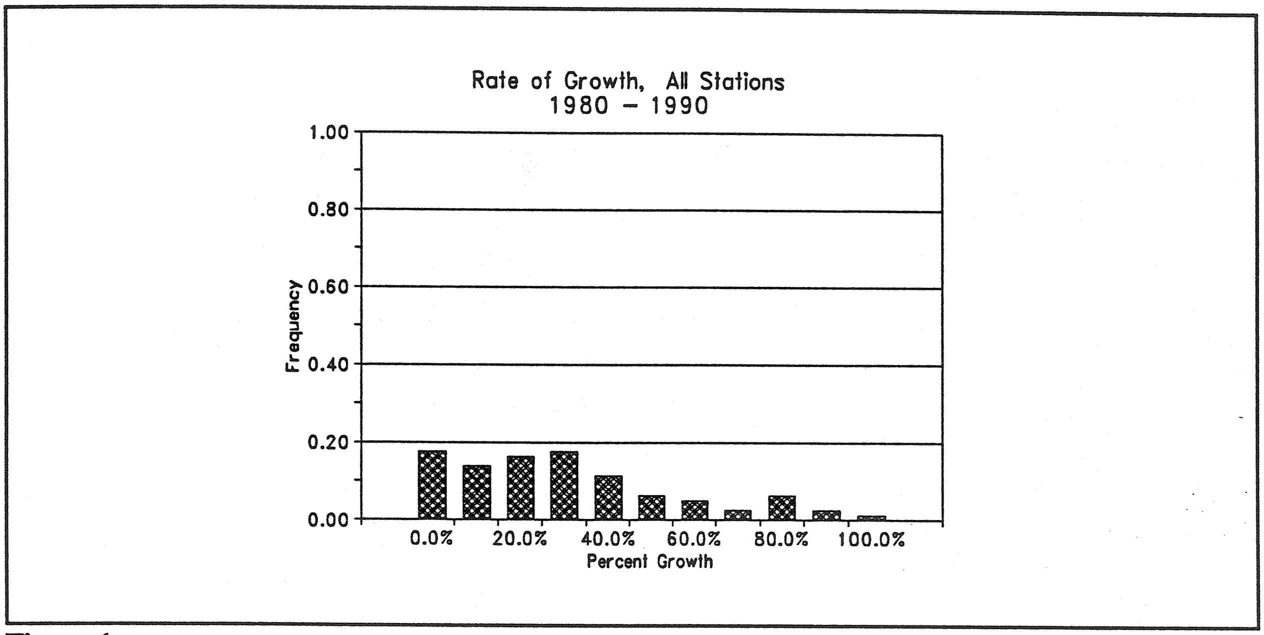


Figure 1

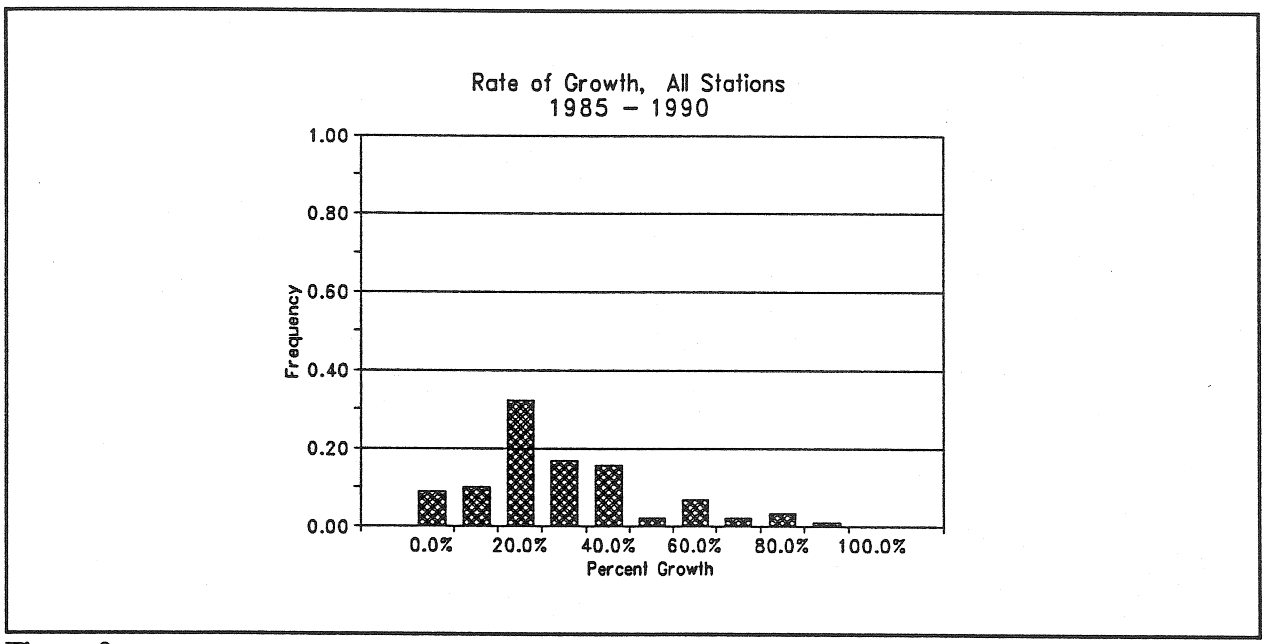


Figure 2

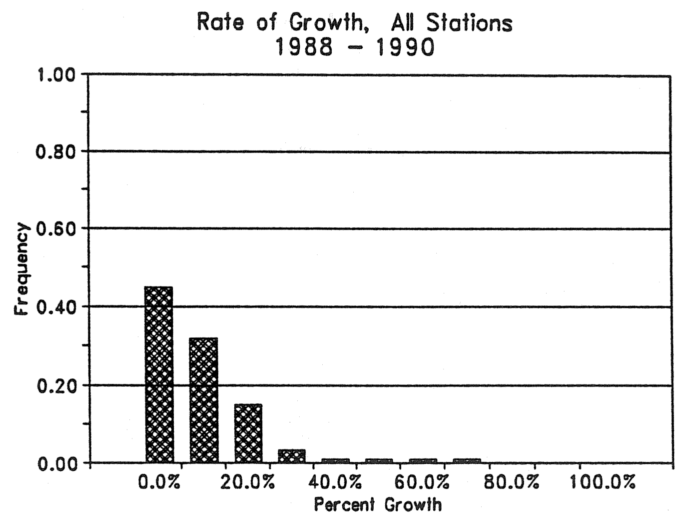

Rate of Growth, All Stations
1988 - 1990
Frequency
1.00
0.80
0.60
0.40
0.20
0.00
0.0%
20.0%
40.0%
60.0%
80.0%
100.0%
Percent Growth

Figure 3

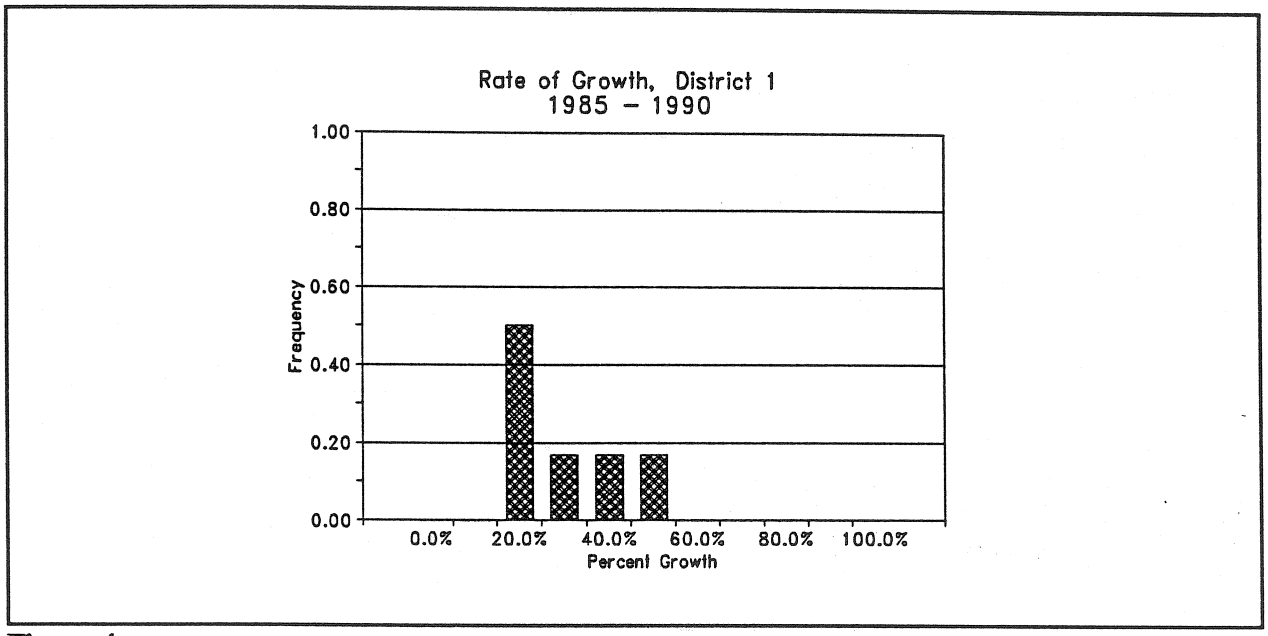


Figure 4

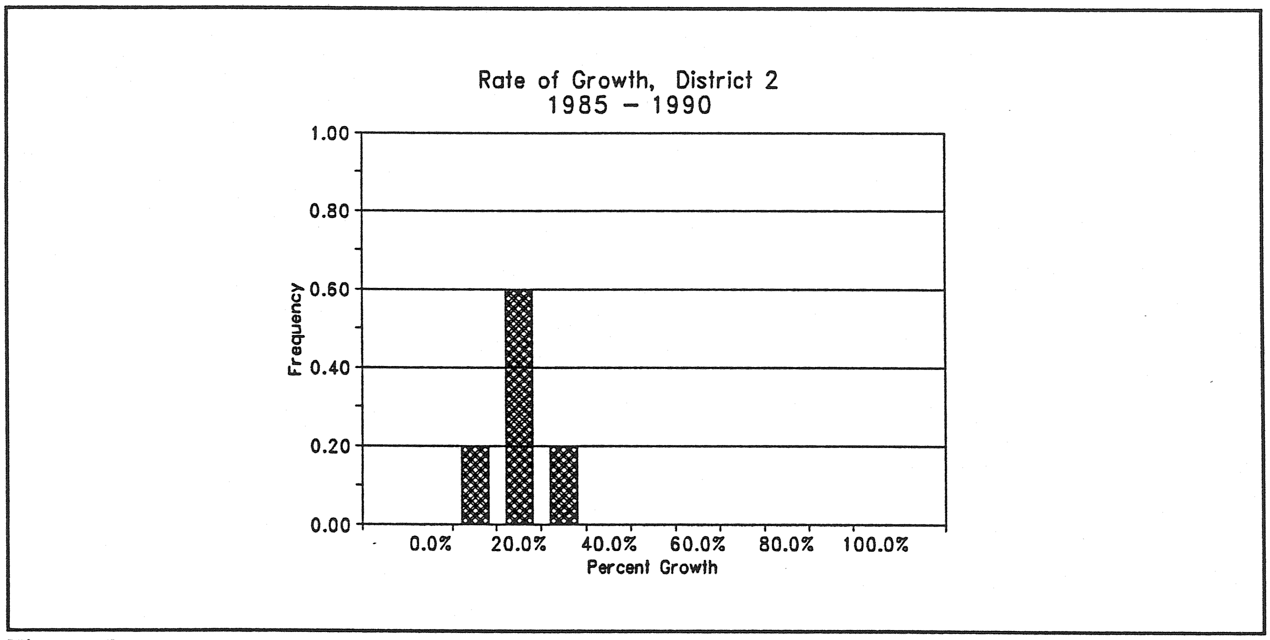
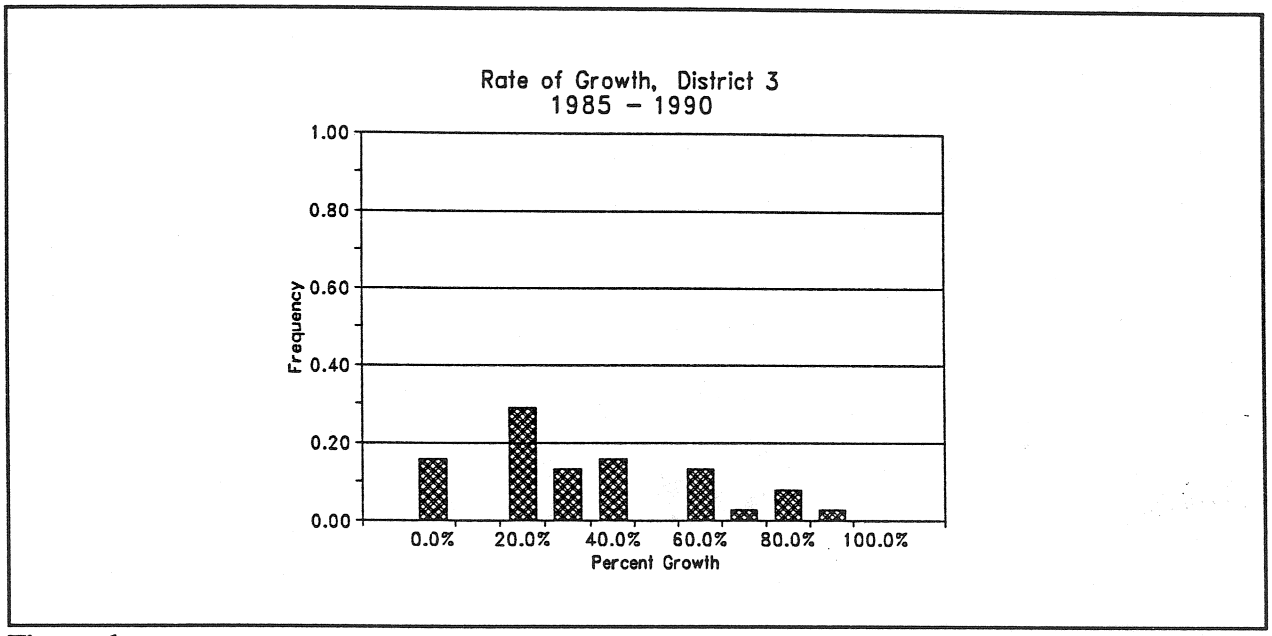
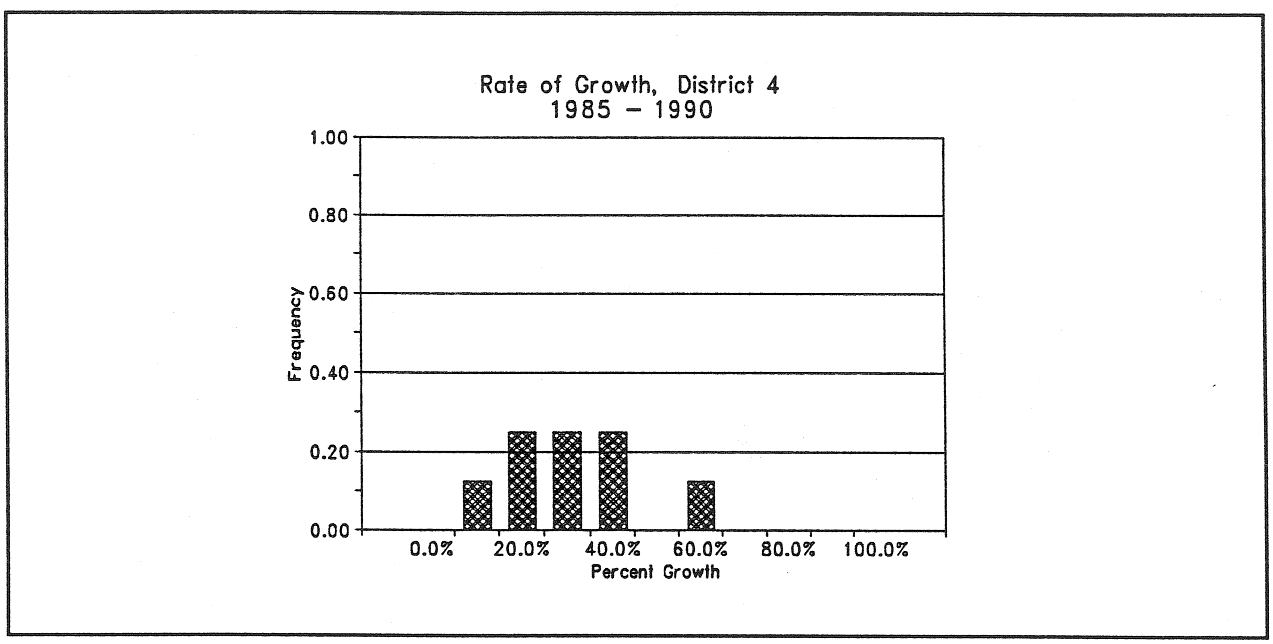


Figure 5

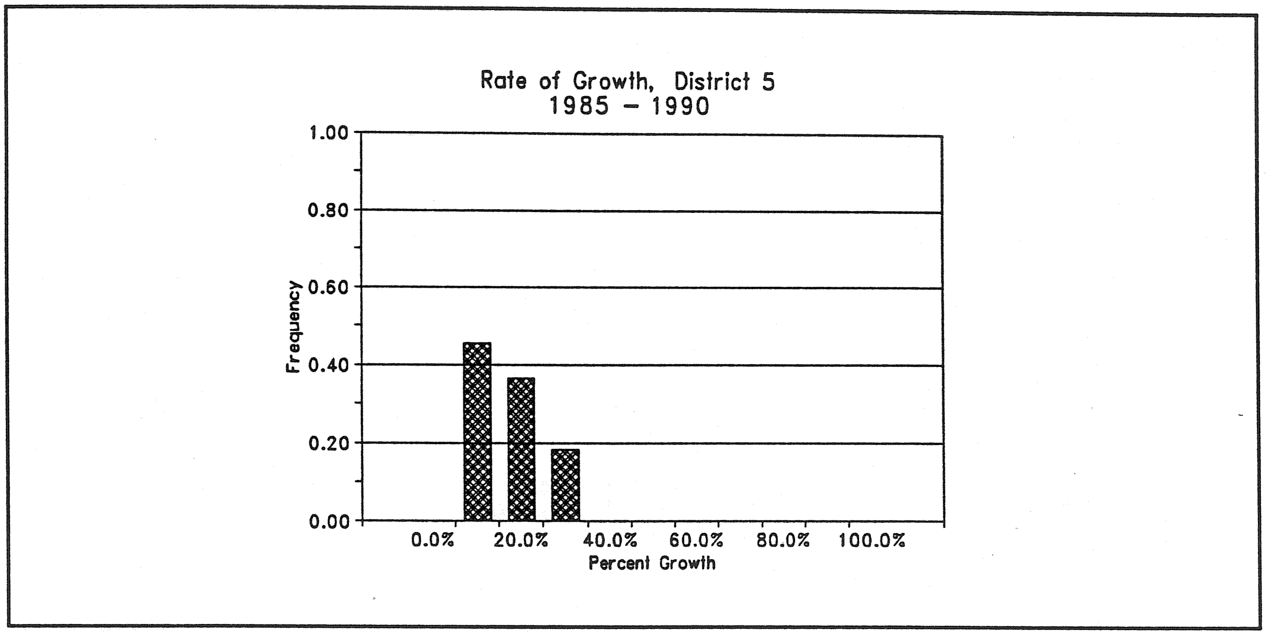


Rate of Growth, District 3
1985 - 1990
1.00
0.80
0.60
0.40
0.20
0.00
Frequency
0.0%
20.0%
40.0%
60.0%
80.0%
100.0%
Percent Growth

Figure 6



Rate of Growth, District 4
1985 - 1990
1.00
0.80
0.60
0.40
0.20
0.00
Frequency
0.0%
20.0%
40.0%
60.0%
80.0%
100.0%
Percent Growth


Rate of Growth, District 5
1985 – 1990
1.00
0.80
0.60
0.40
0.20
0.00
Frequency
0.0%
20.0%
40.0%
60.0%
80.0%
100.0%
Percent Growth

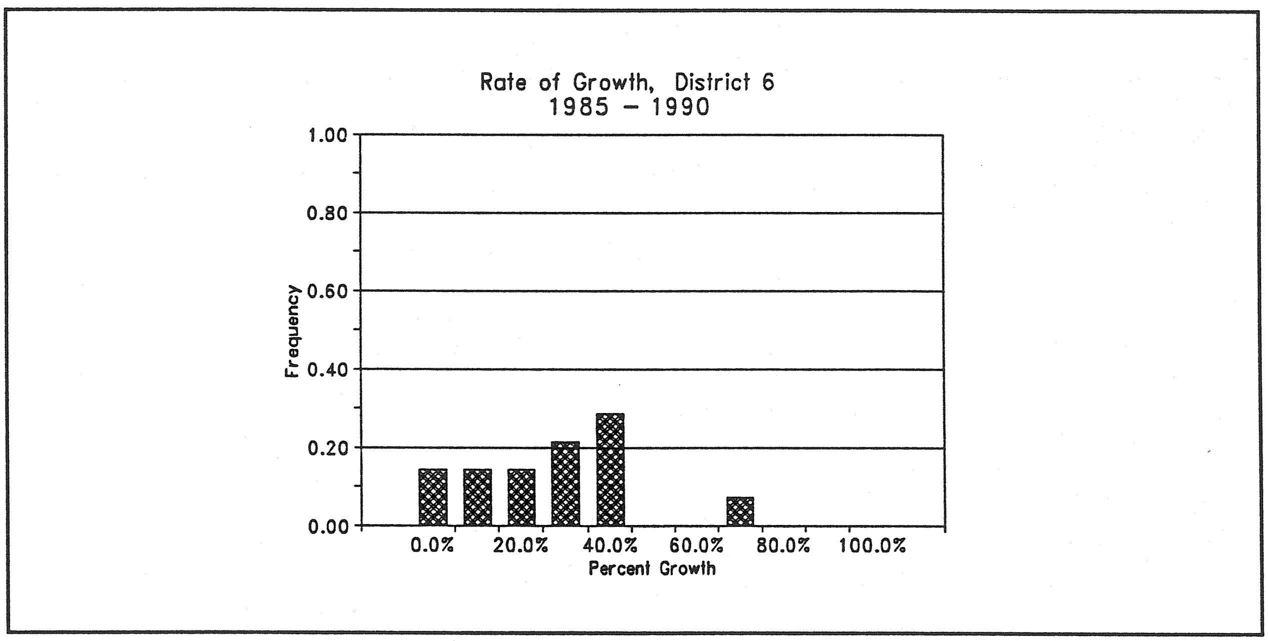

Rate of Growth, District 6
1985 – 1990
1.00
0.80
0.60
0.40
0.20
0.00
Frequency
0.0%
20.0%
40.0%
60.0%
80.0%
100.0%
Percent Growth

Figure 9

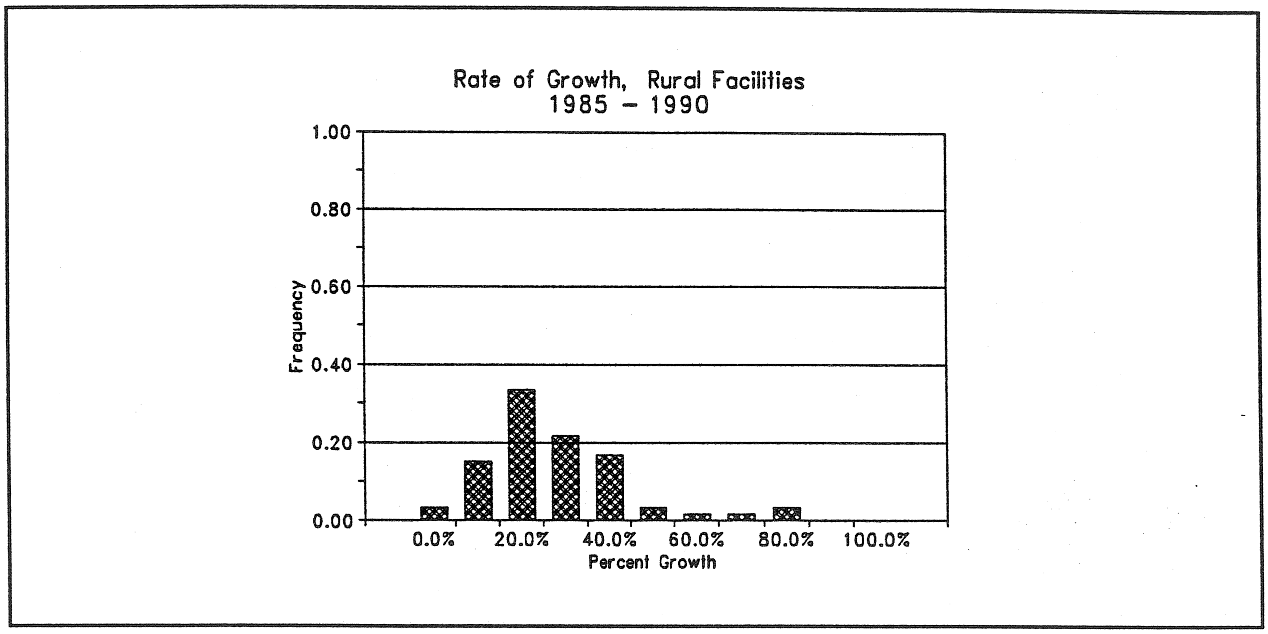


Figure 10

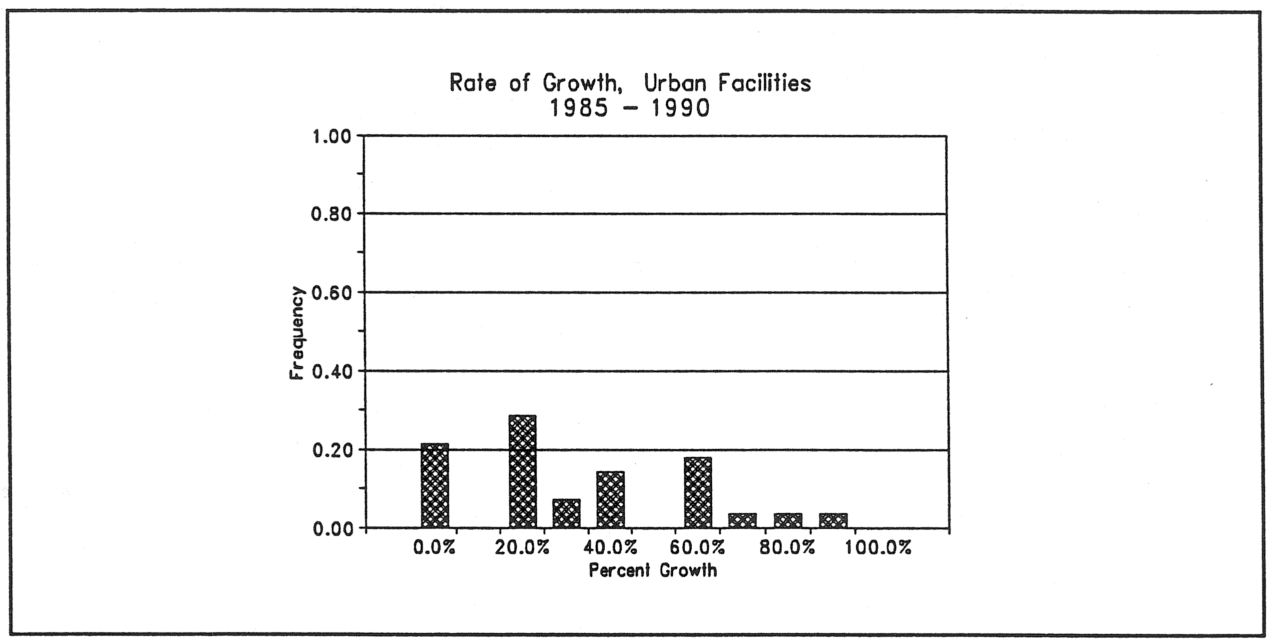


Figure 11

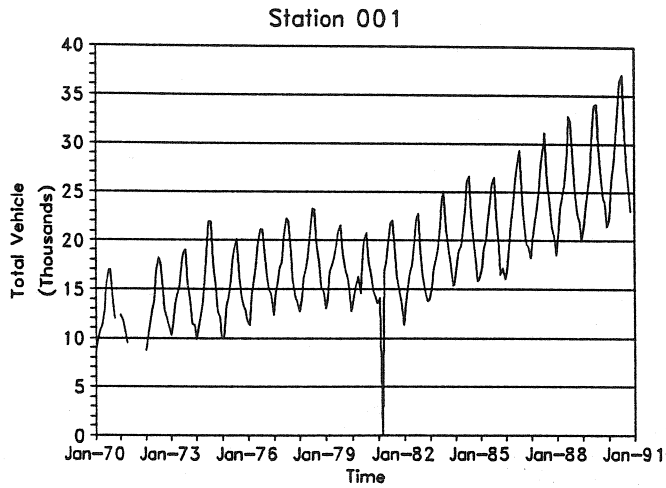
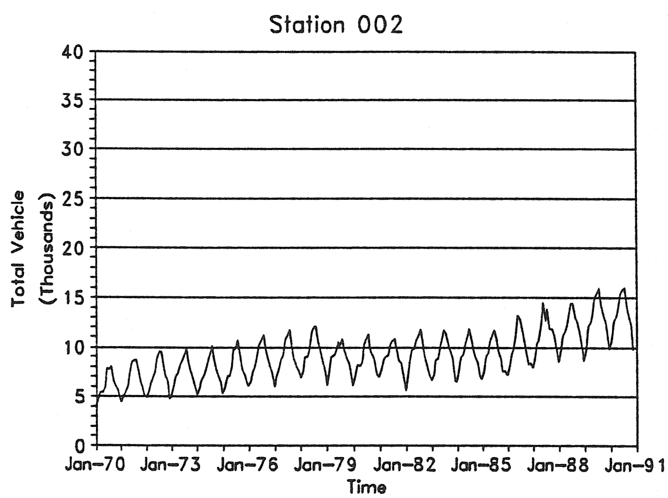


Figure 1



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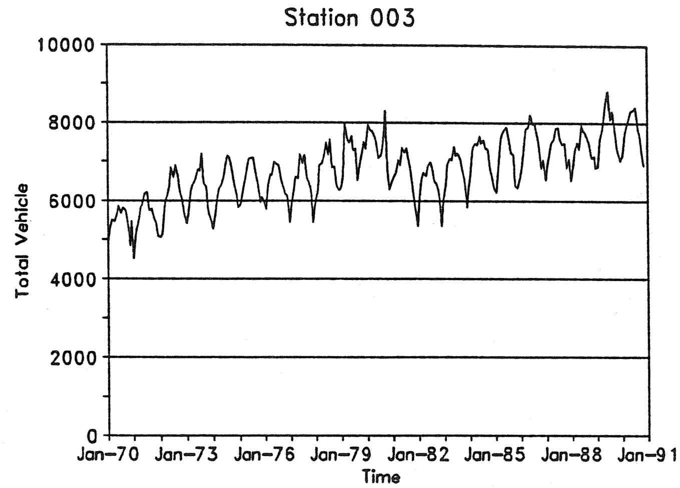
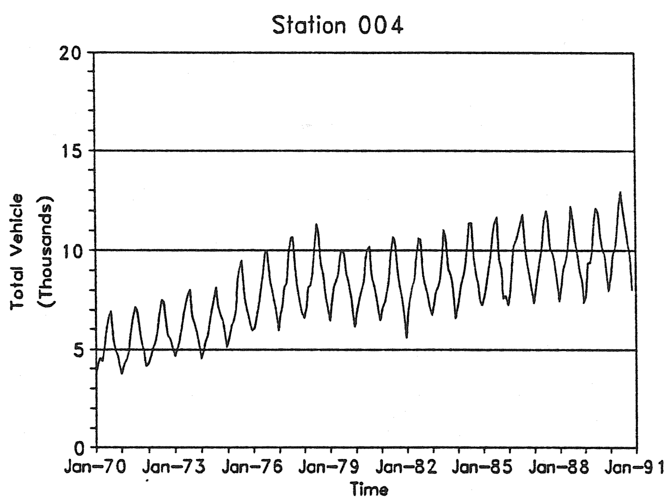


Figure 3



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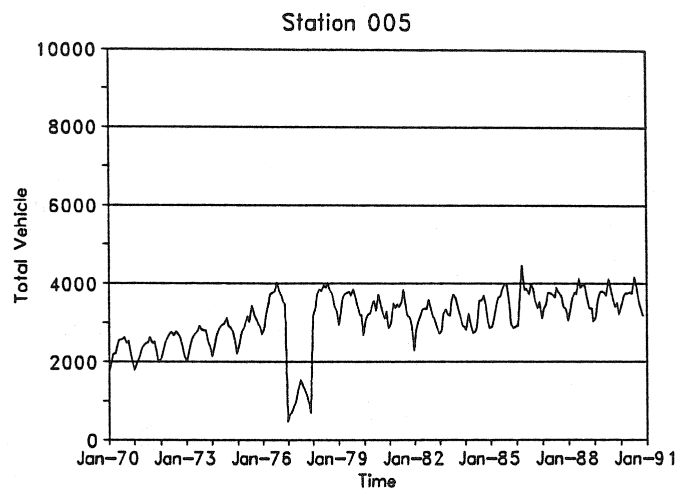

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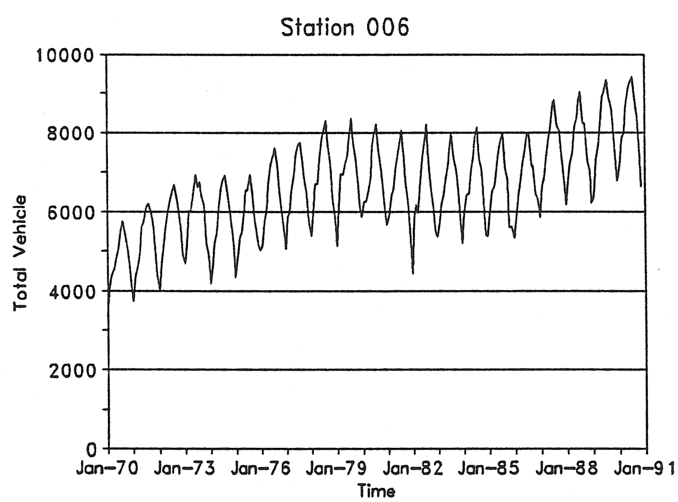
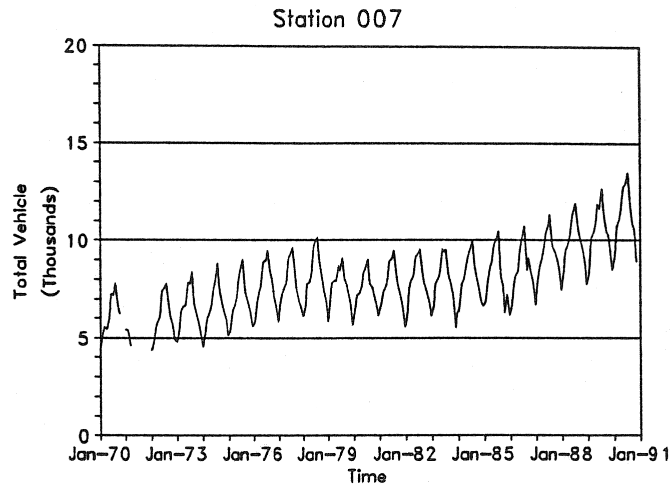


Figure 6



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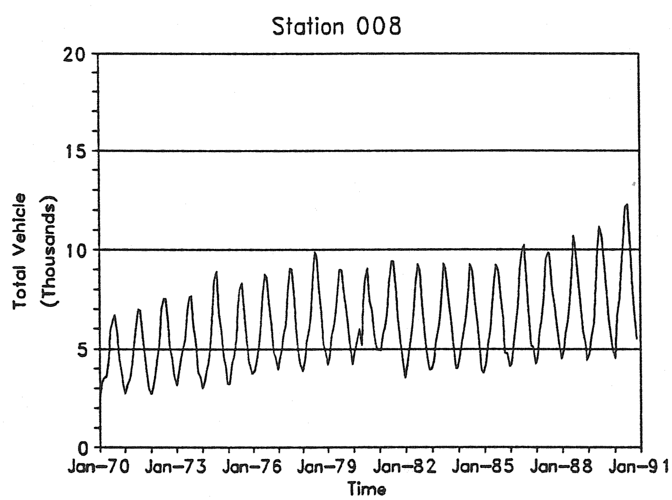

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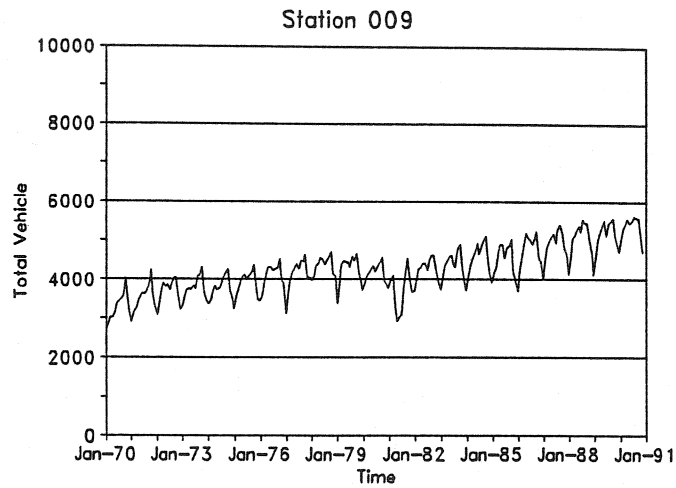

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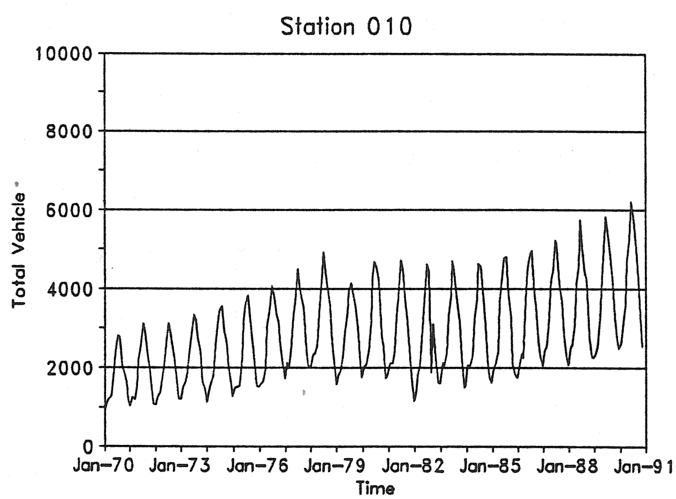


Figure 10

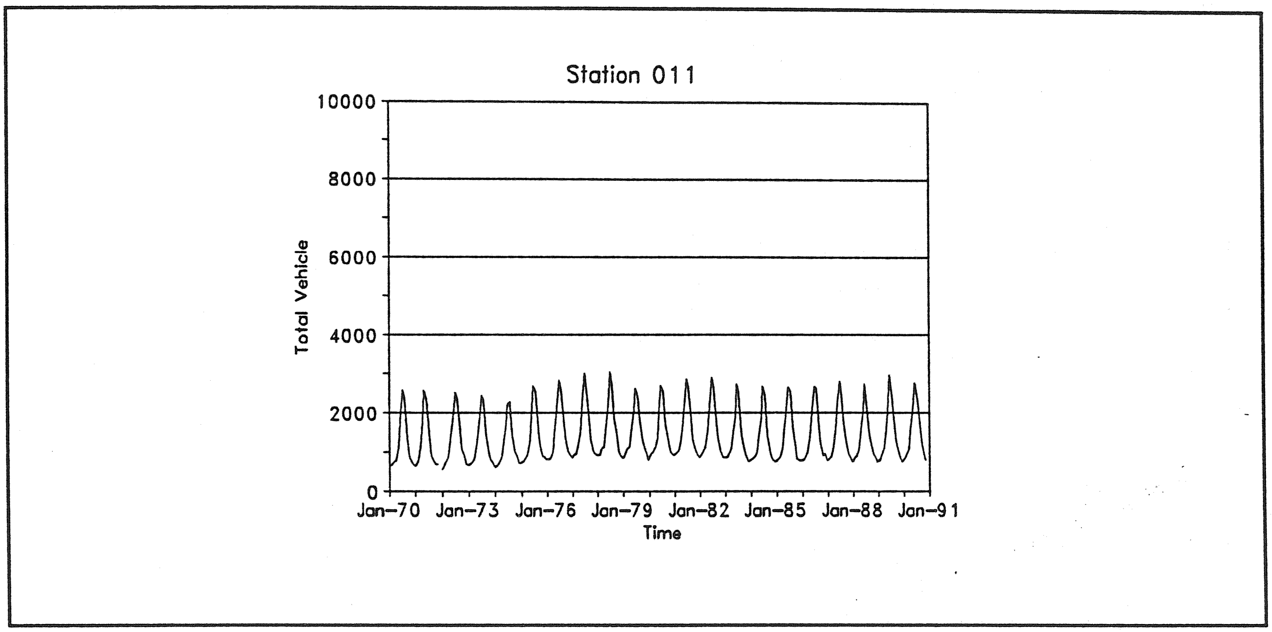


Figure 11

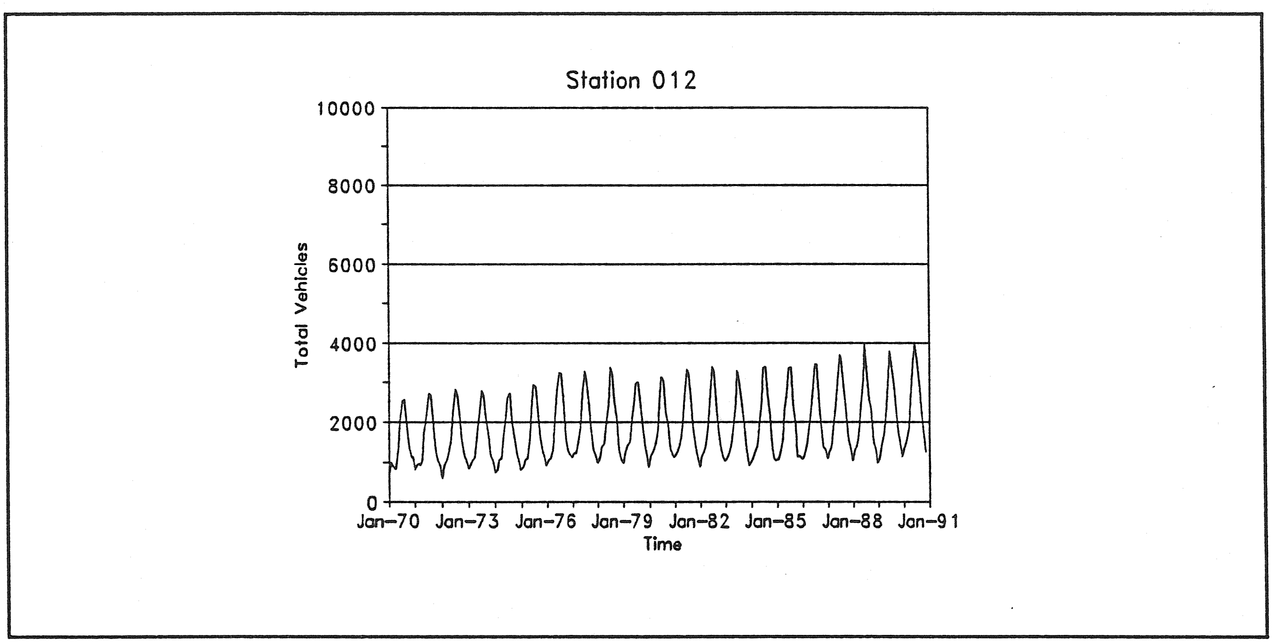


Figure 12

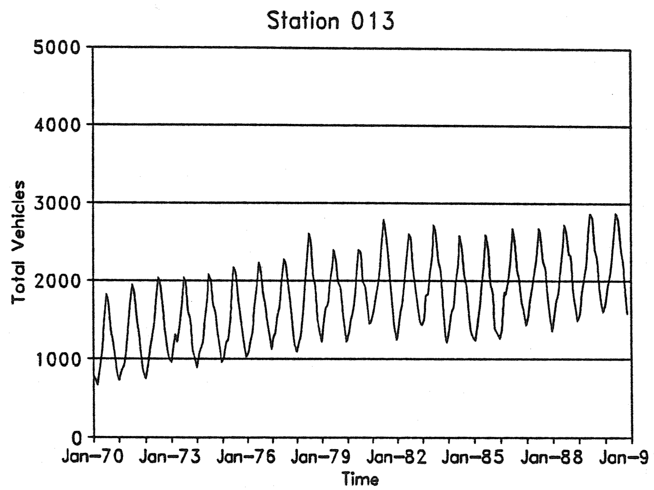
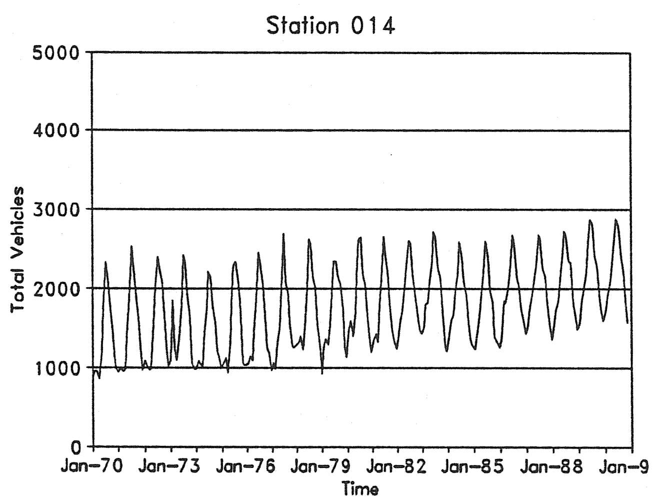
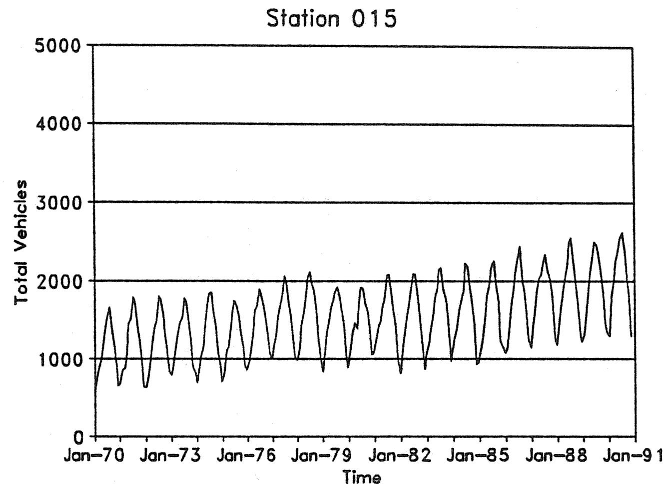

Station 013
5000
4000
3000
2000
1000
0
Total Vehicles
Jan-70 Jan-73 Jan-76 Jan-79 Jan-82 Jan-85 Jan-88 Jan-91
Time

Figure 13


Station 014
5000
4000
3000
2000
1000
0
Total Vehicles
Jan-70 Jan-73 Jan-76 Jan-79 Jan-82 Jan-85 Jan-88 Jan-91
Time



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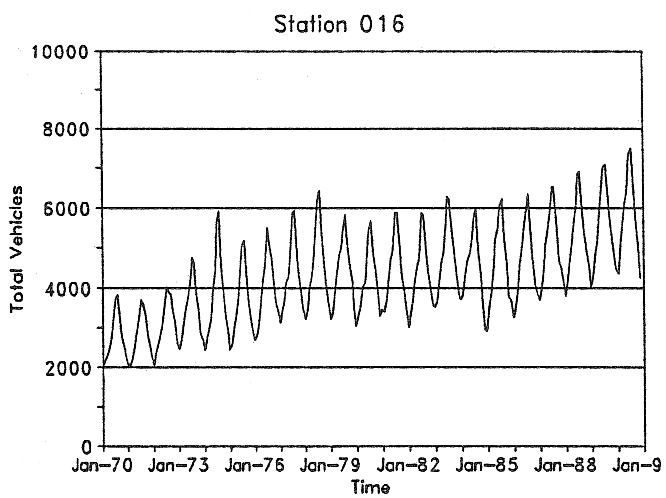


Figure 16

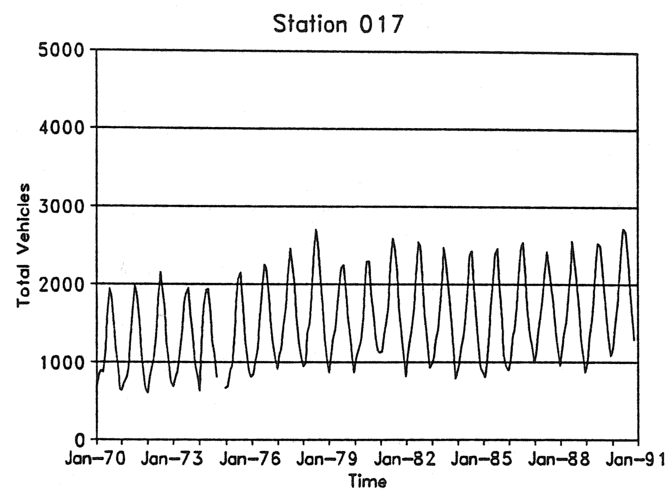
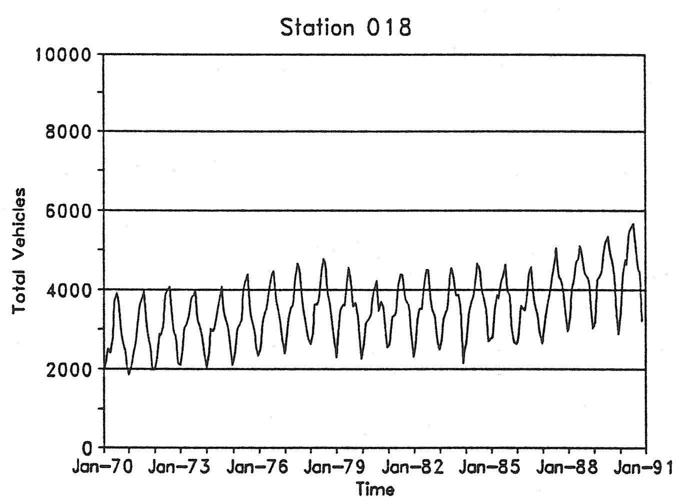


Figure 17



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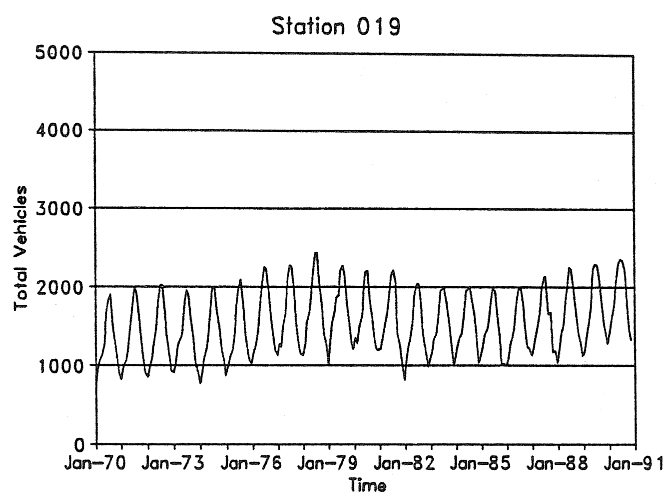

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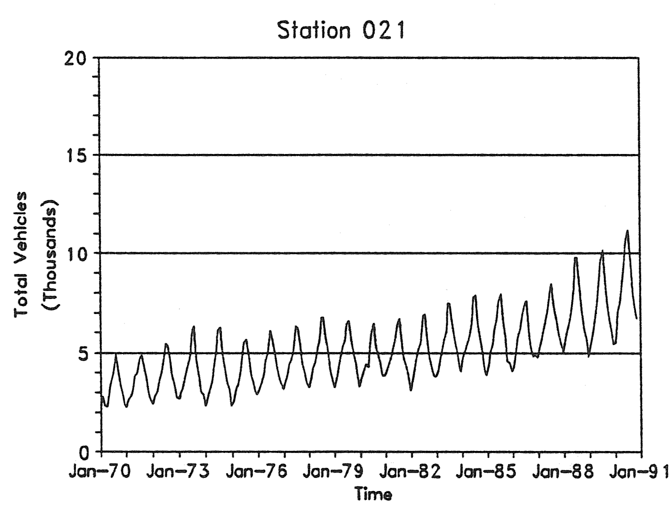

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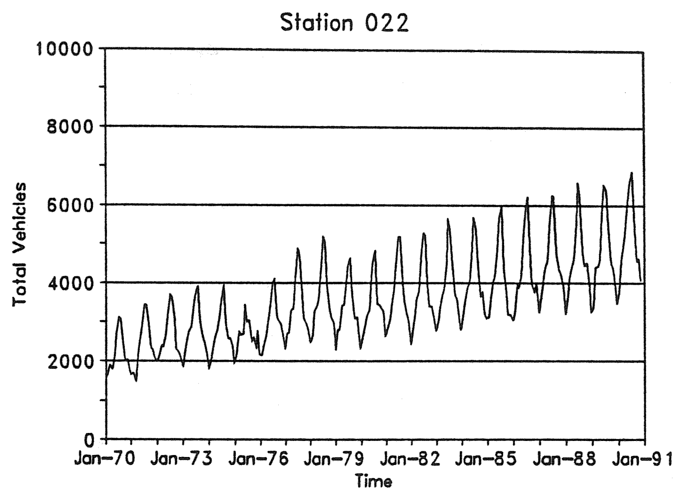


Figure 21

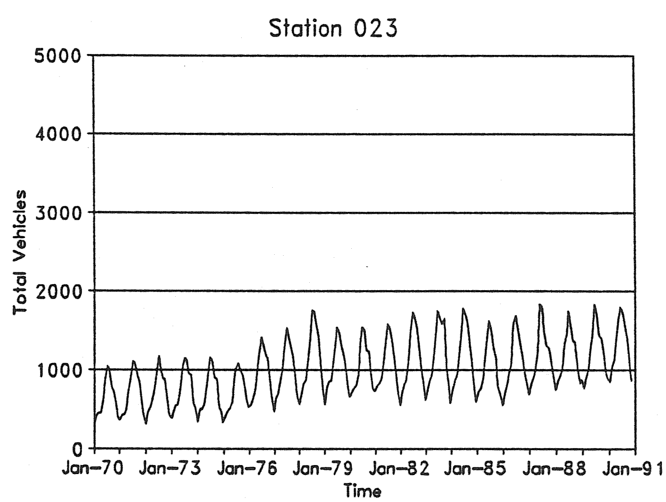


Figure 22

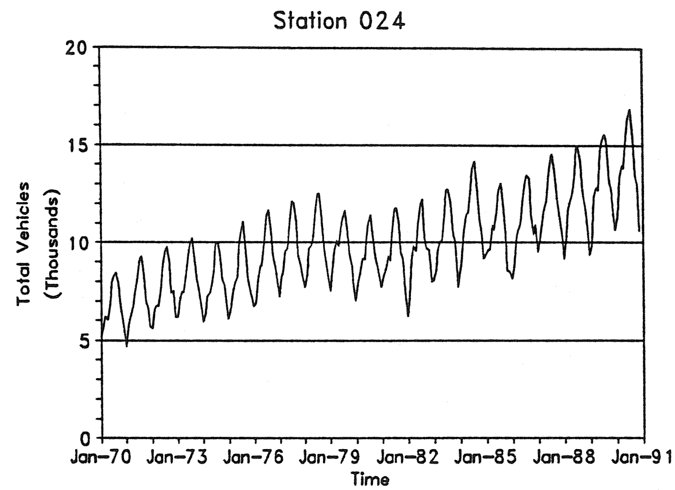


Figure 23

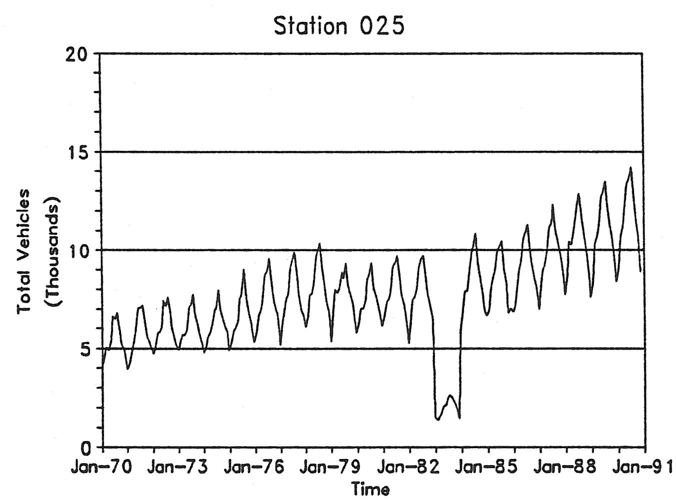


Figure 24

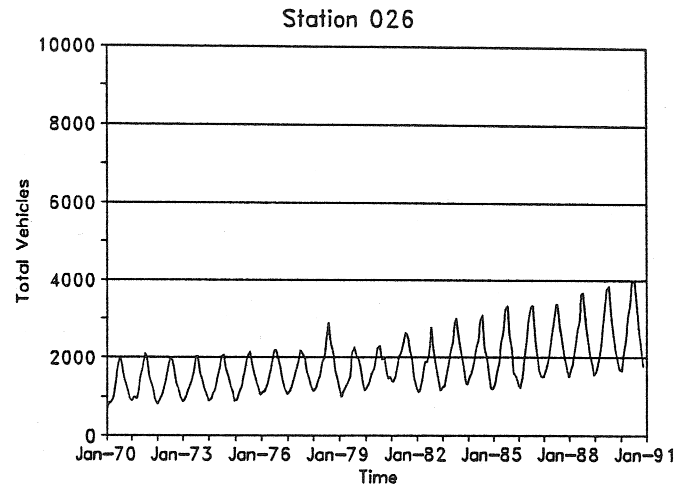


Figure 25

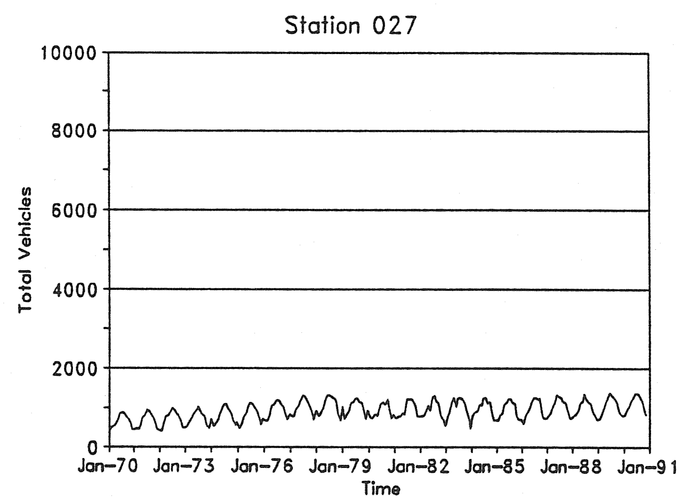


Figure 26

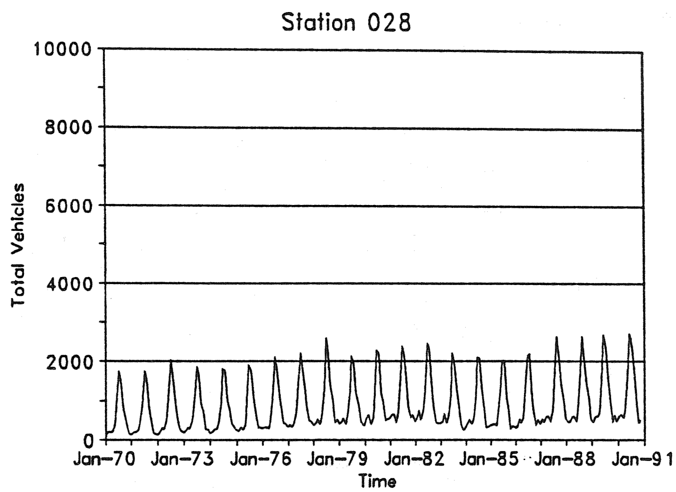


Figure 27

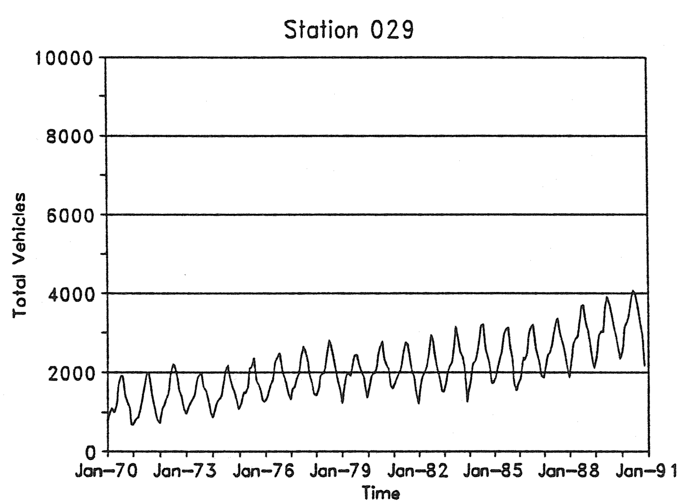


Figure 28

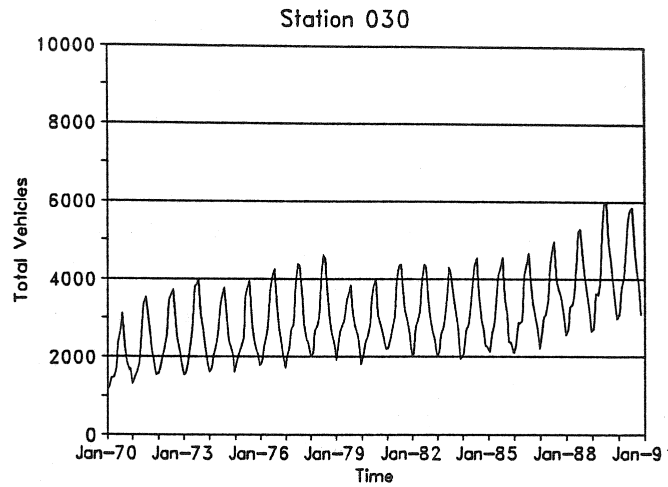


Figure 29

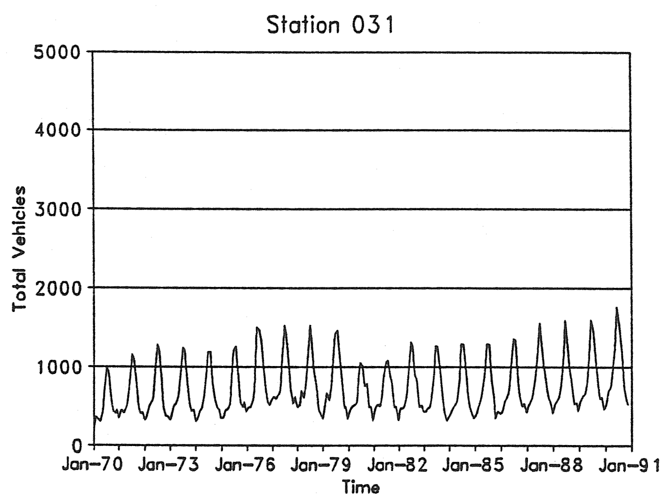


Figure 30

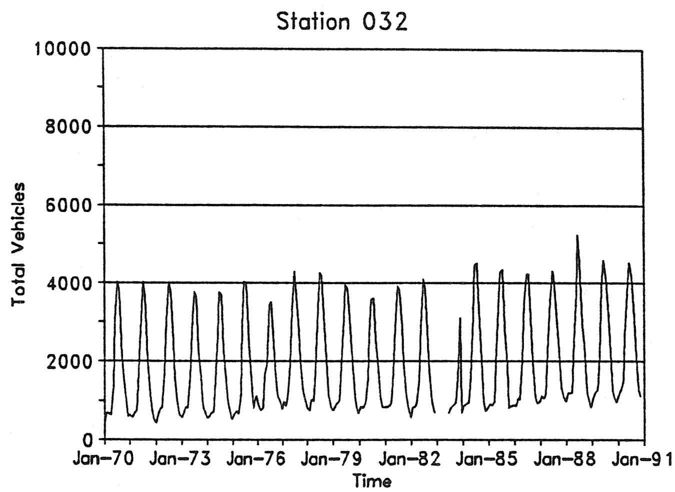


Figure 31

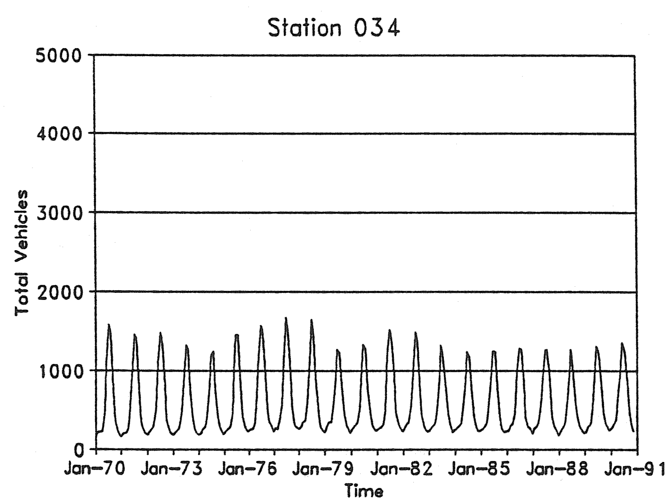


Figure 32

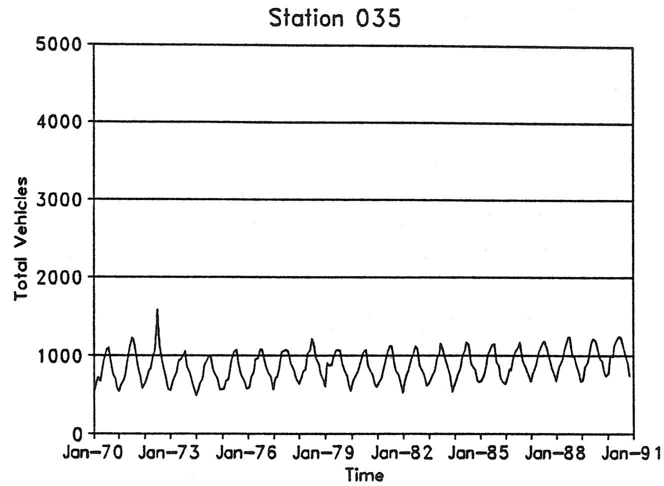


Figure 33

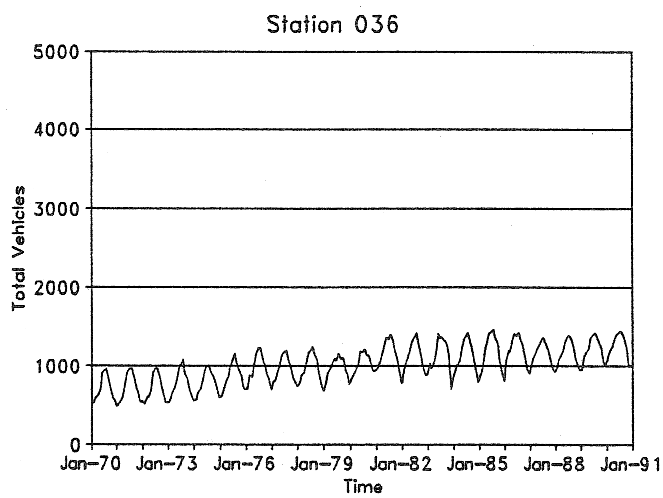


Figure 34

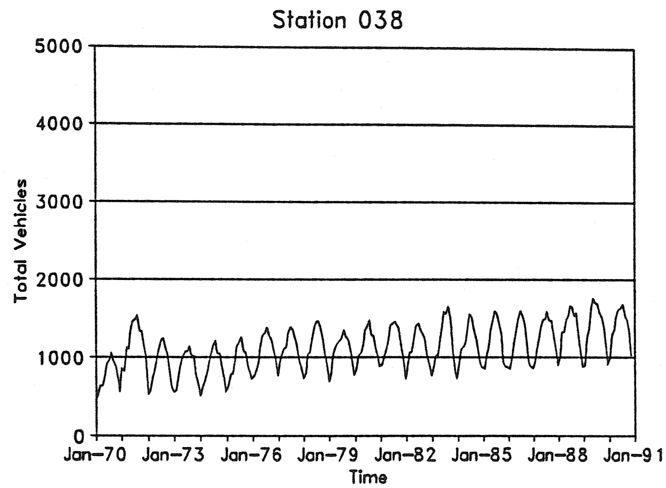


Figure 35

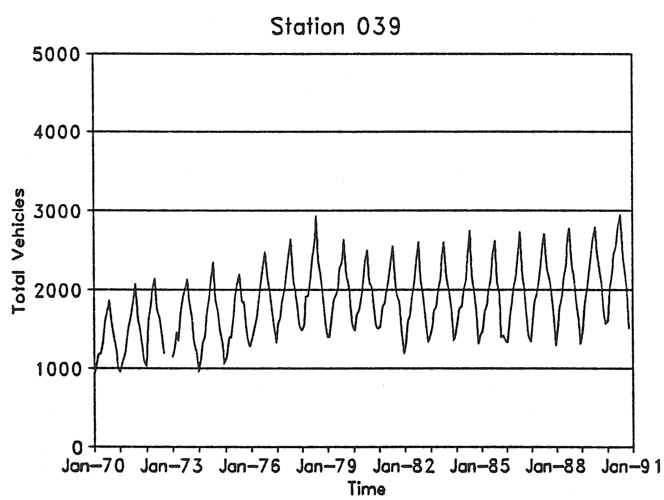


Figure 36

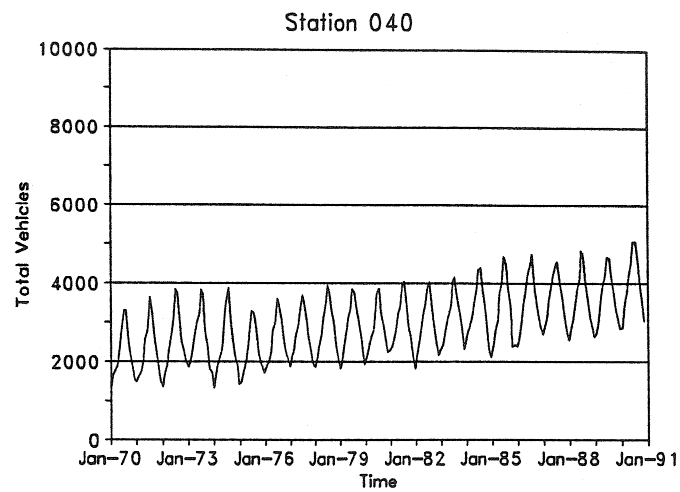


Figure 37

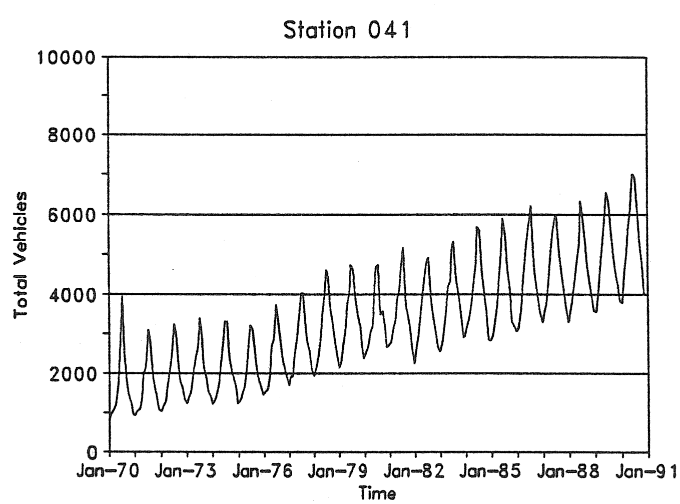


Figure 38

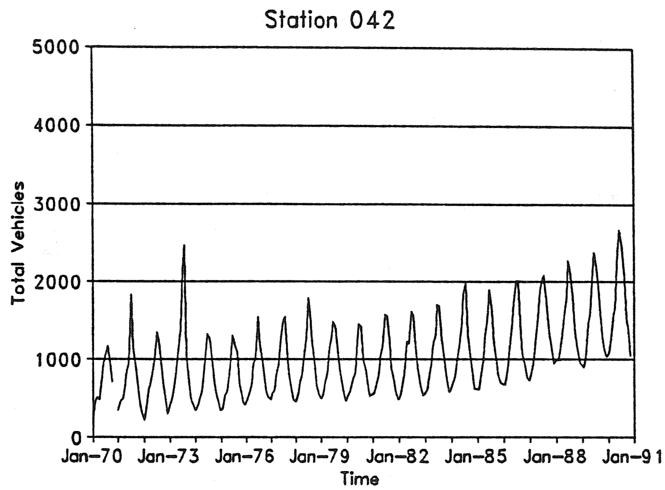
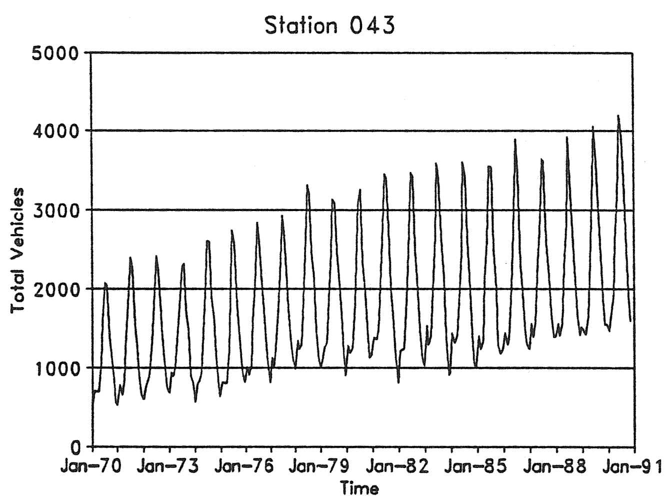


Figure 39



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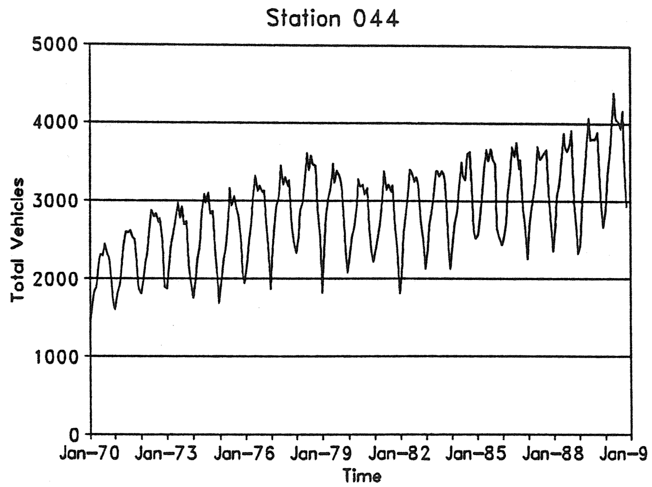


Figure 41

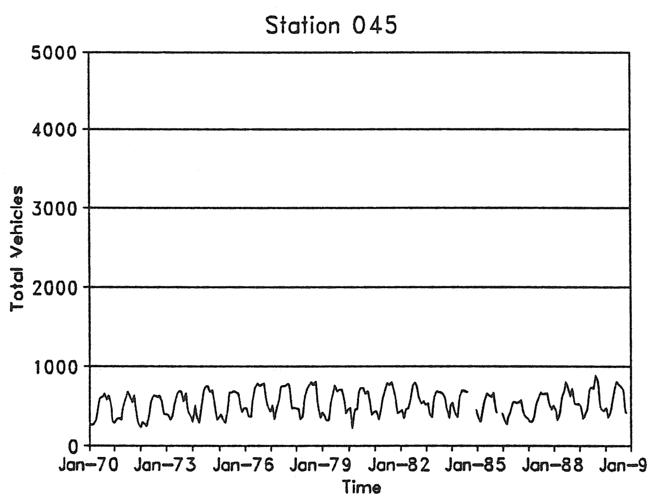


Figure 42

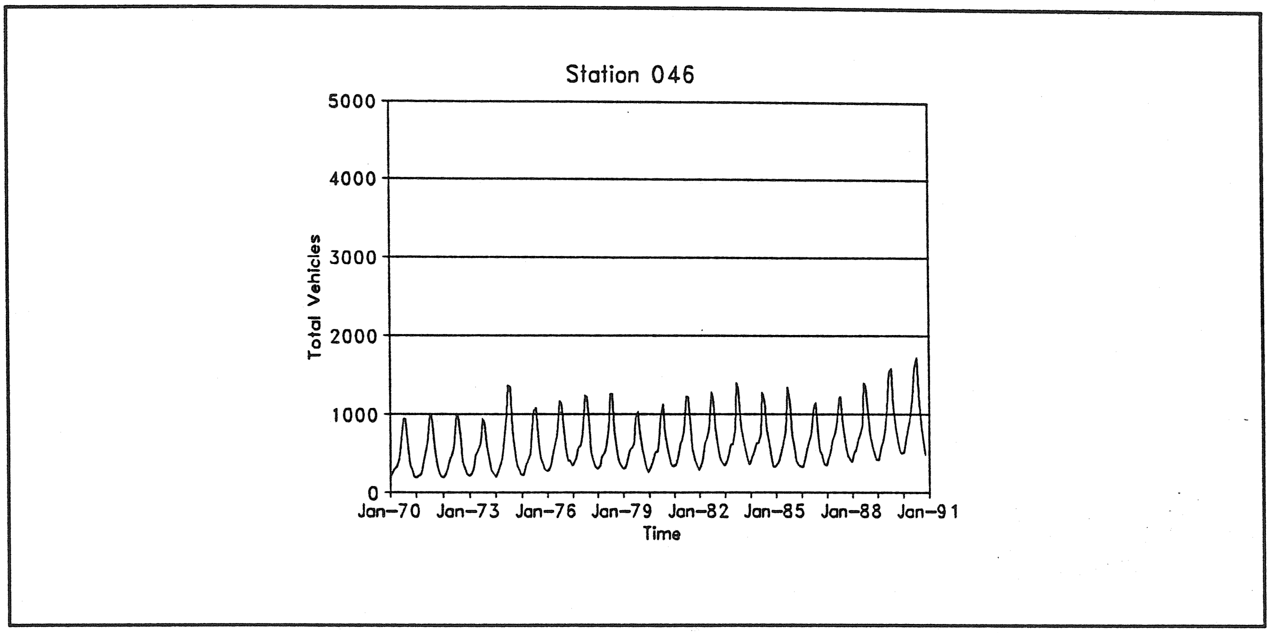


Figure 43

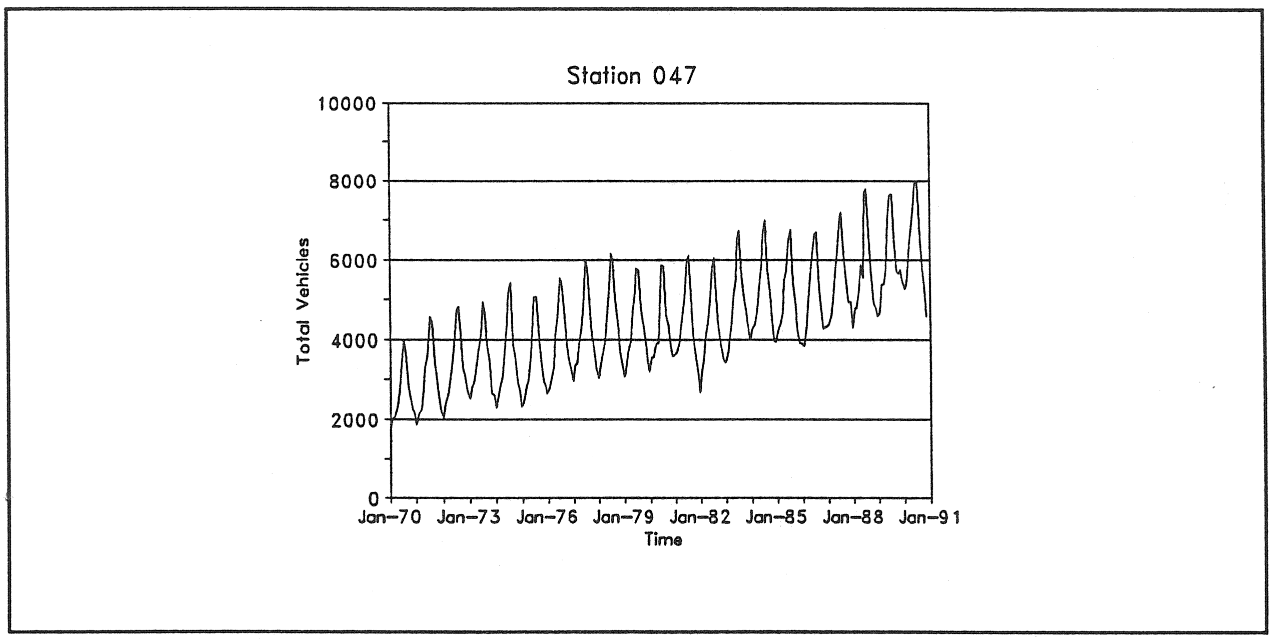
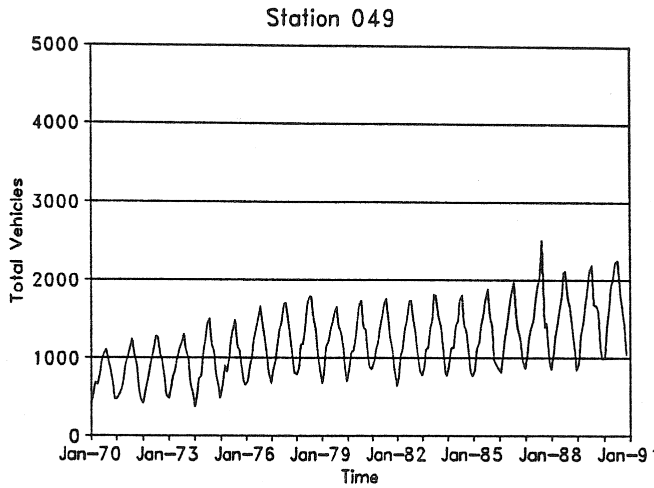


Figure 44



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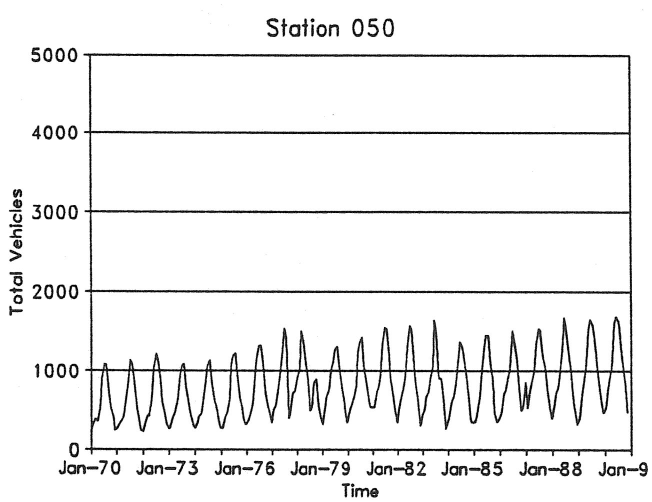


Figure 46

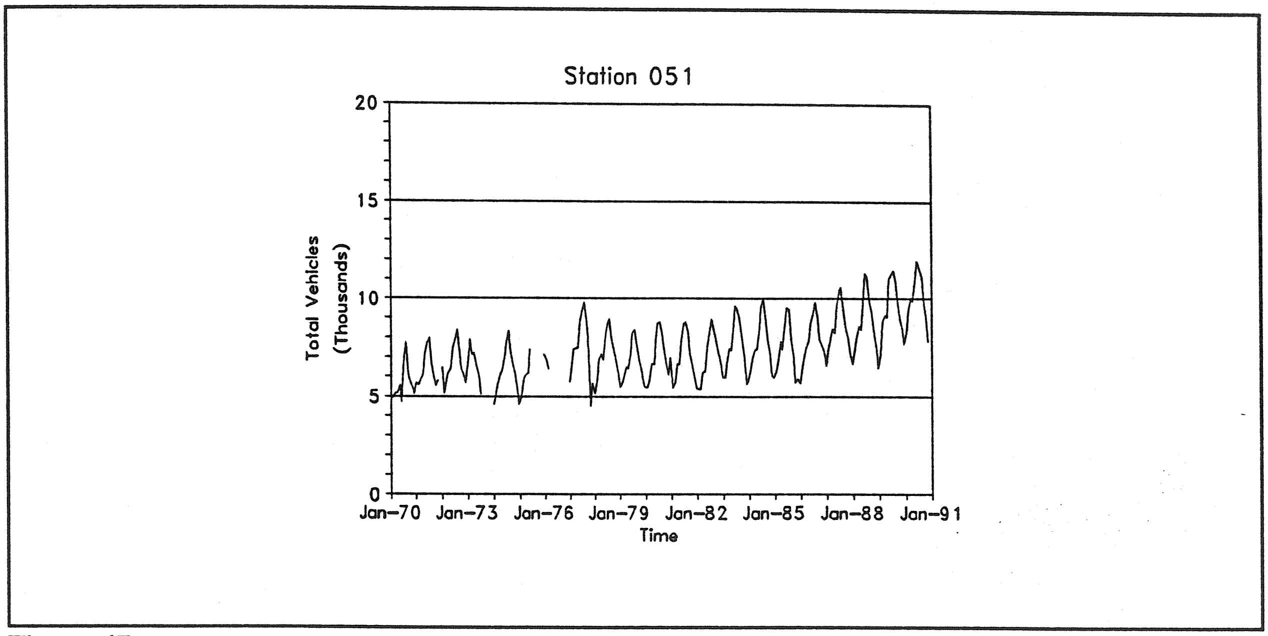


Figure 47

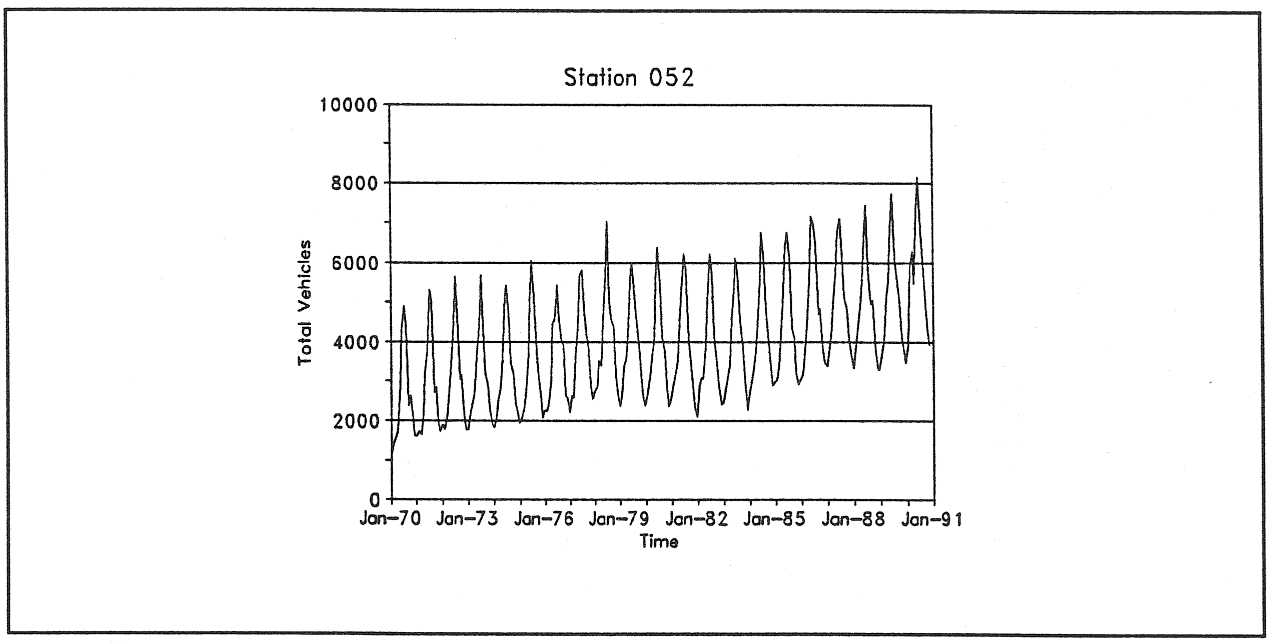


Figure 48

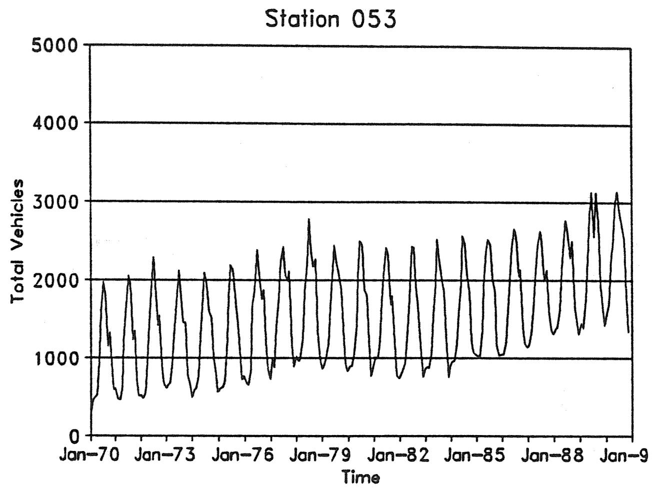


Figure 49

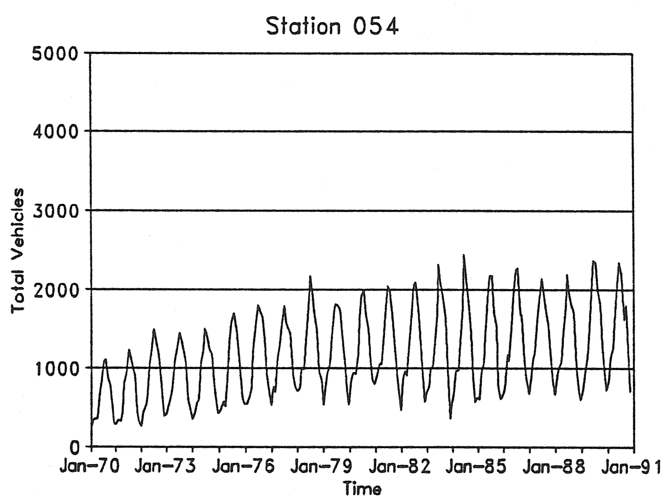


Figure 50

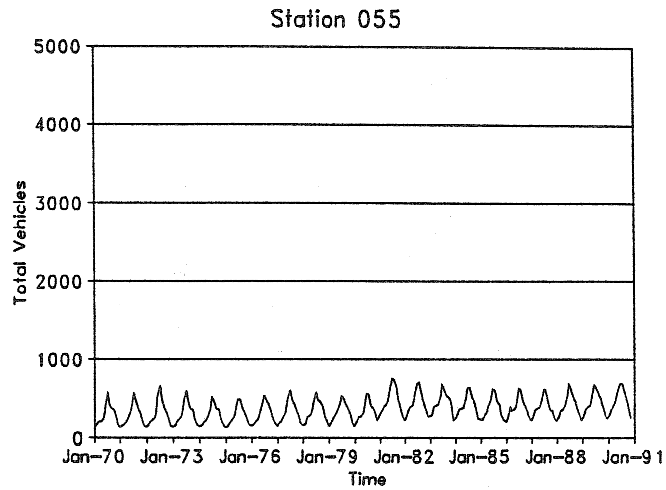
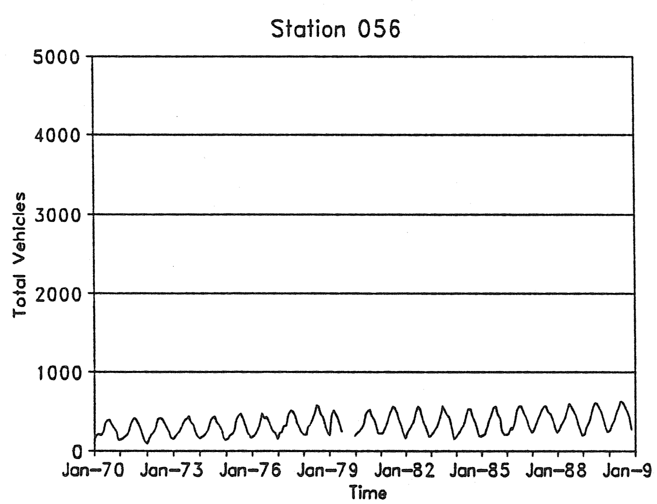


Figure 51



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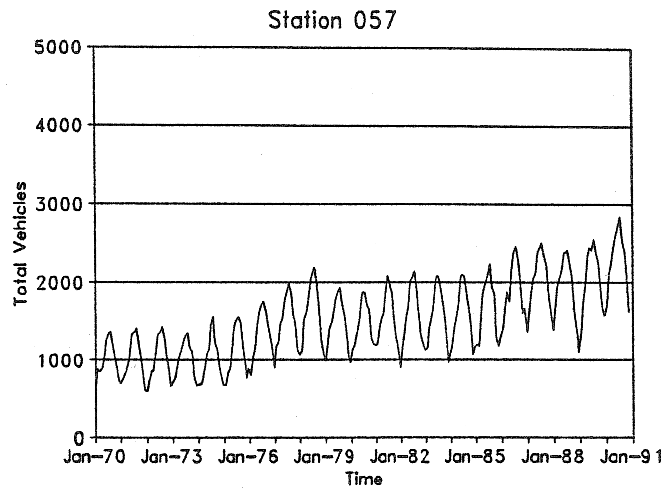


Figure 53

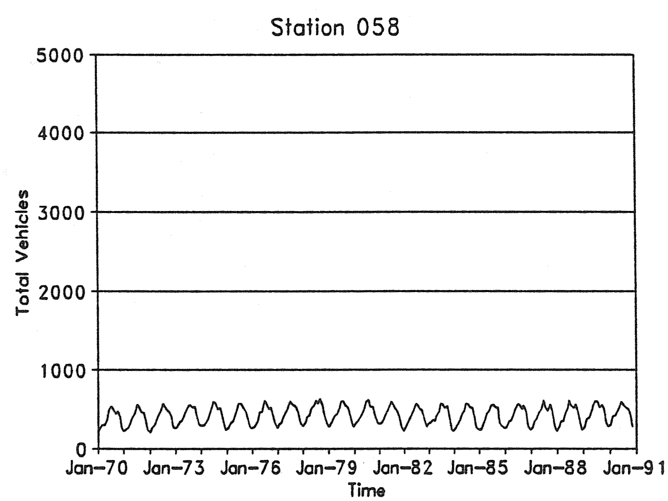


Figure 54

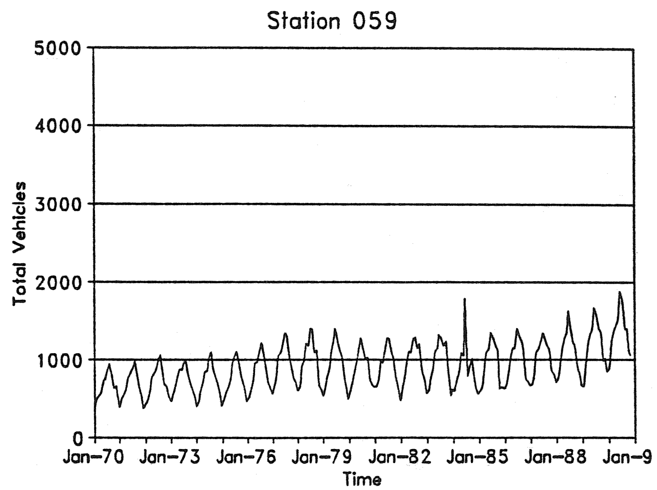
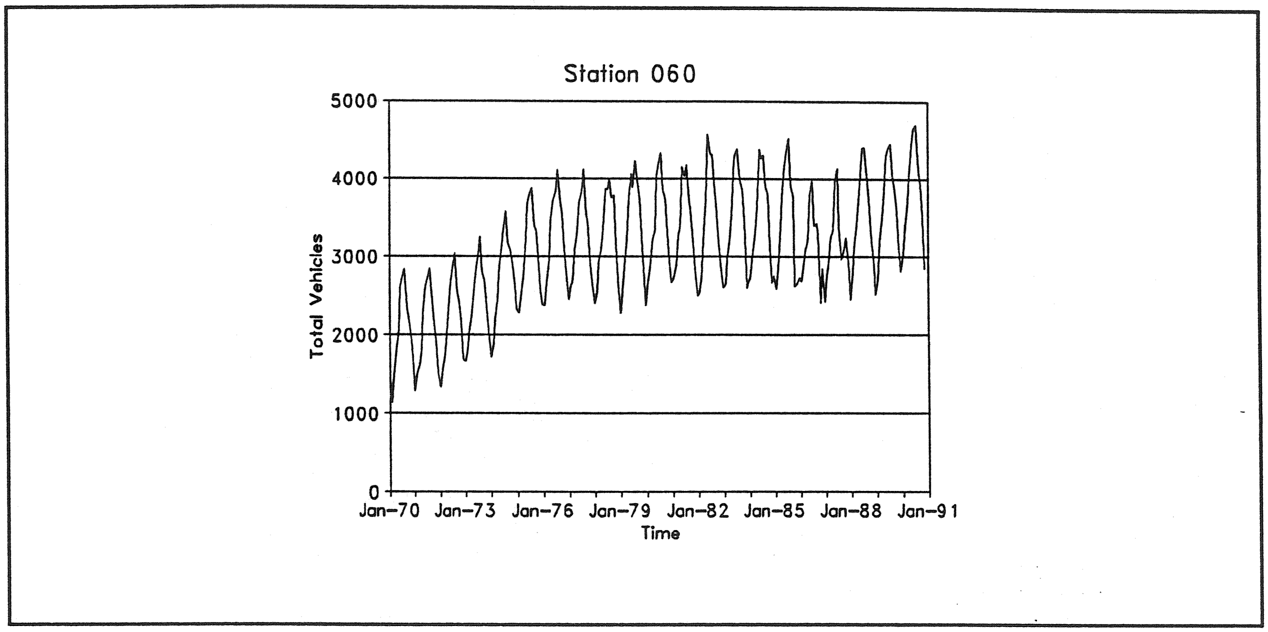

Station 059
5000
4000
3000
2000
1000
0
Total Vehicles
Jan-70 Jan-73 Jan-76 Jan-79 Jan-82 Jan-85 Jan-88 Jan-91
Time

Figure 55



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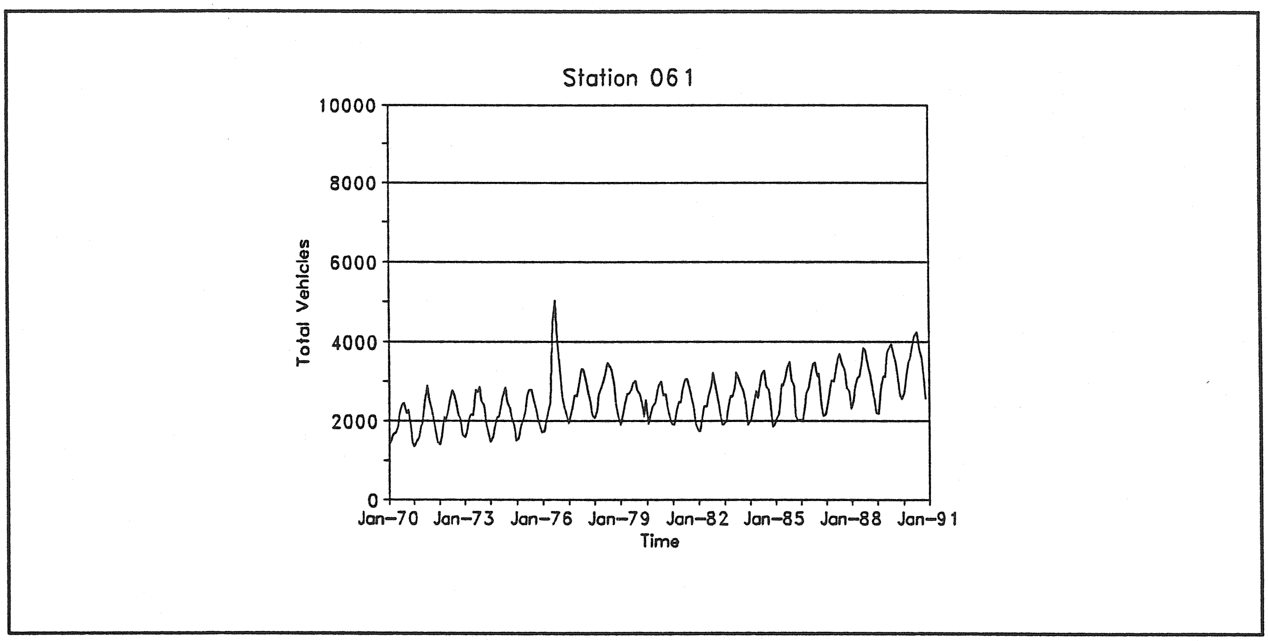

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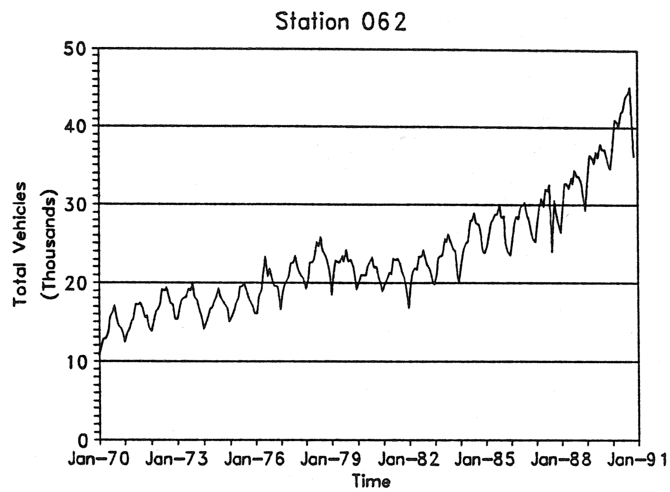

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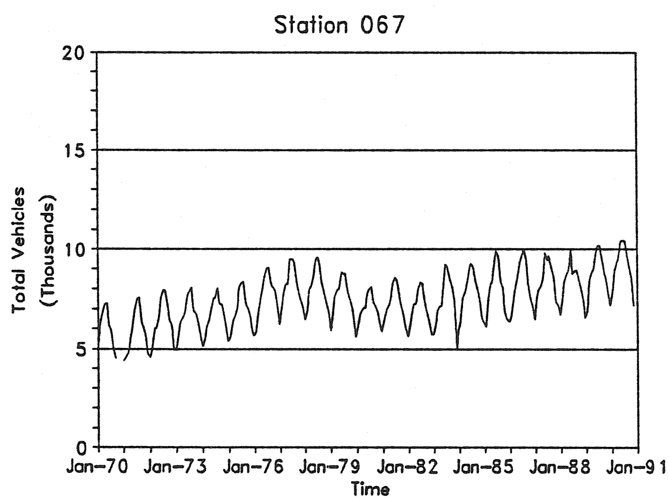


Figure 59

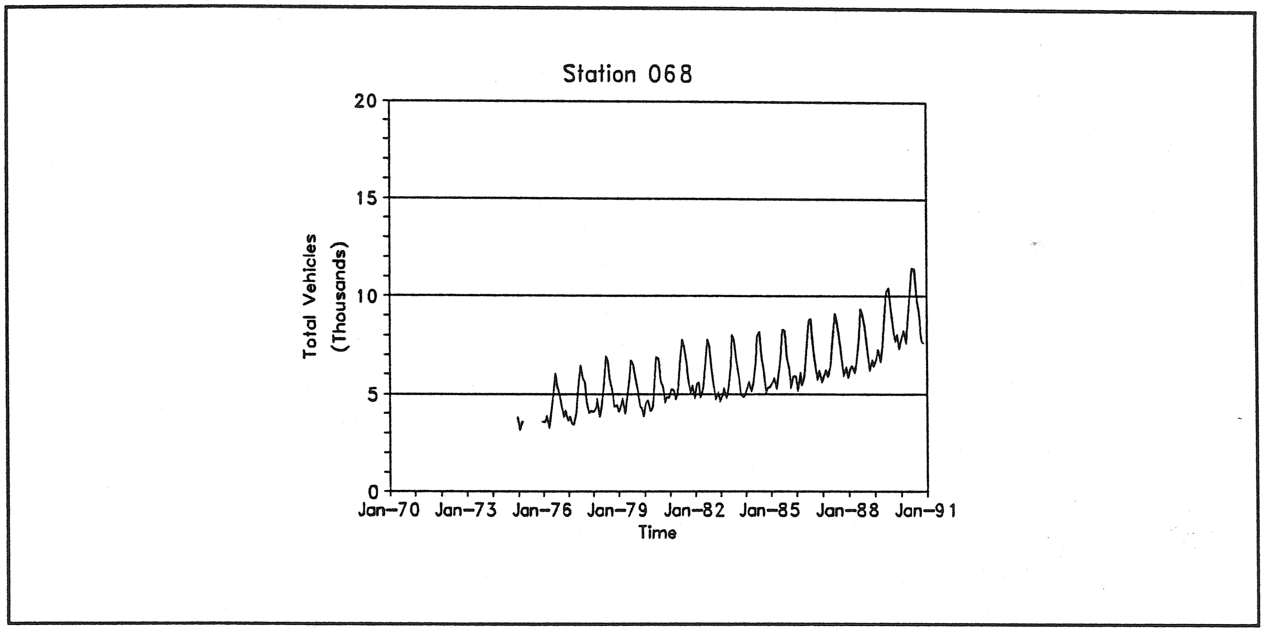
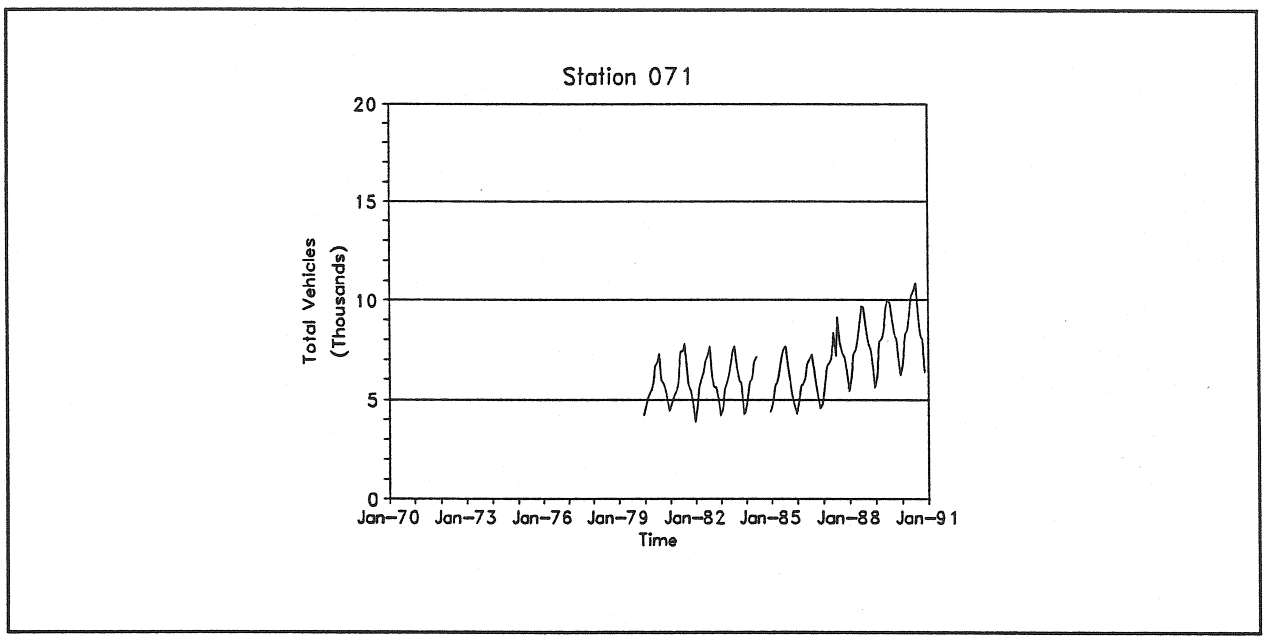


Figure 60



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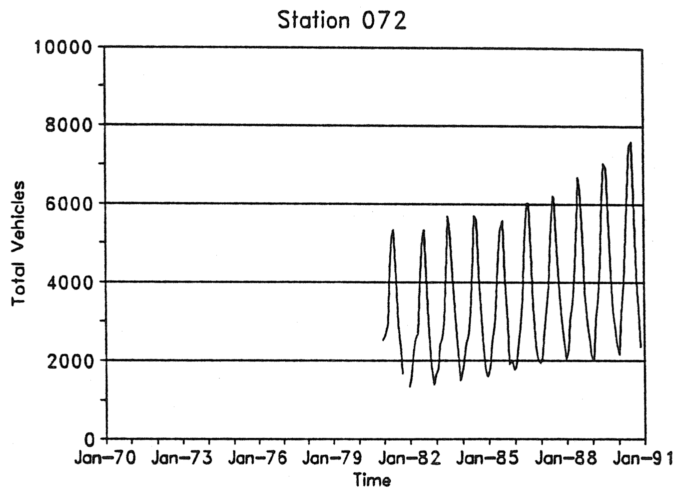


Figure 62

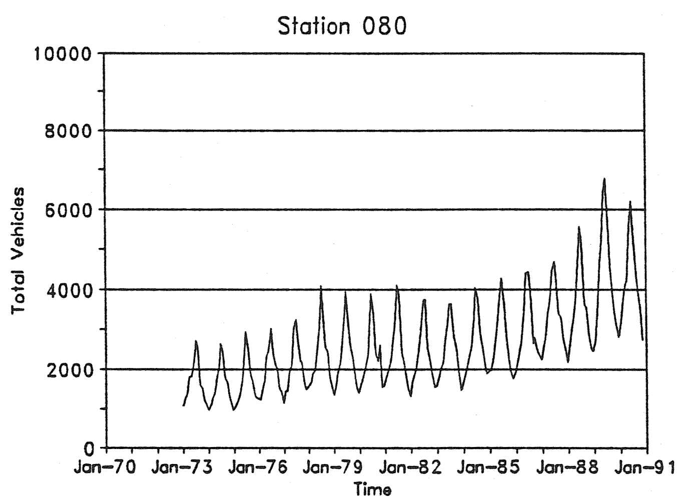


Figure 63

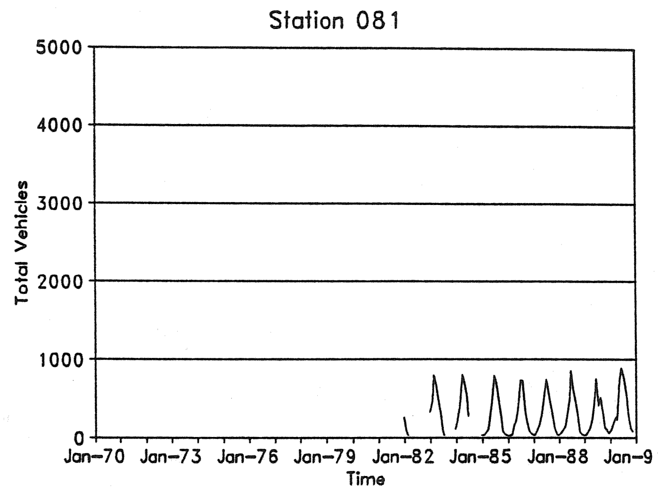
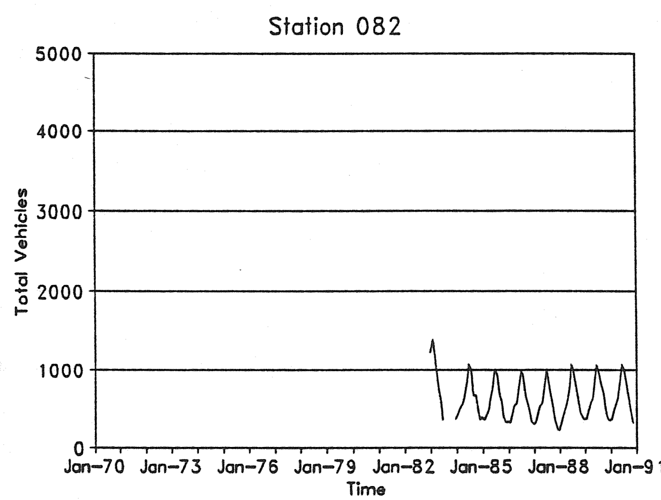


Figure 64



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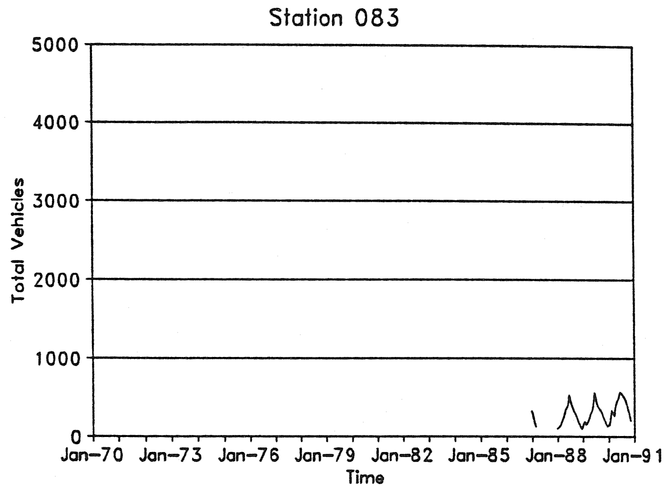

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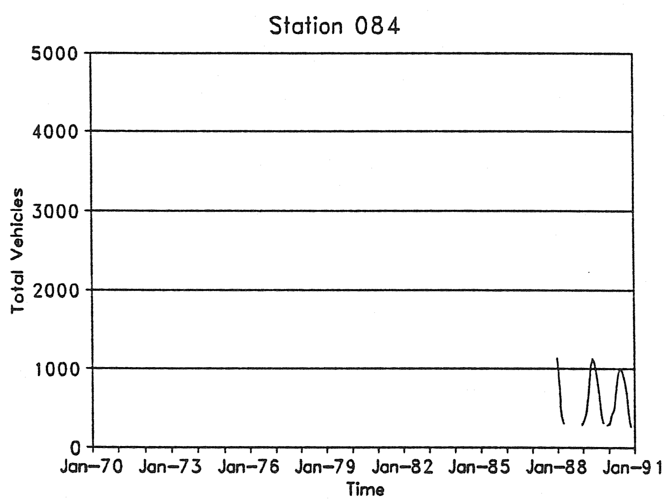

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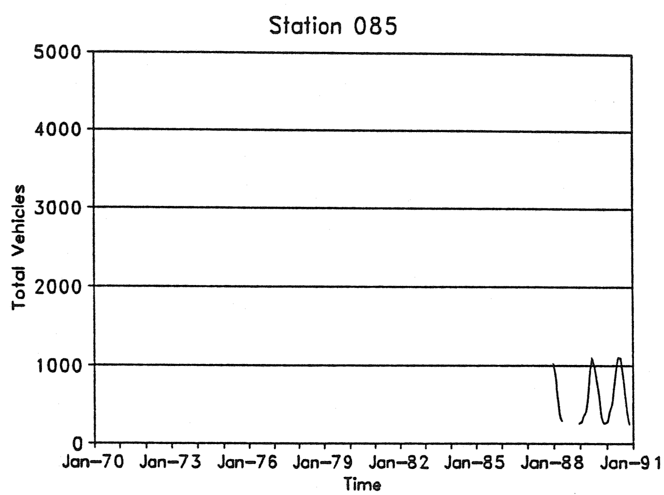

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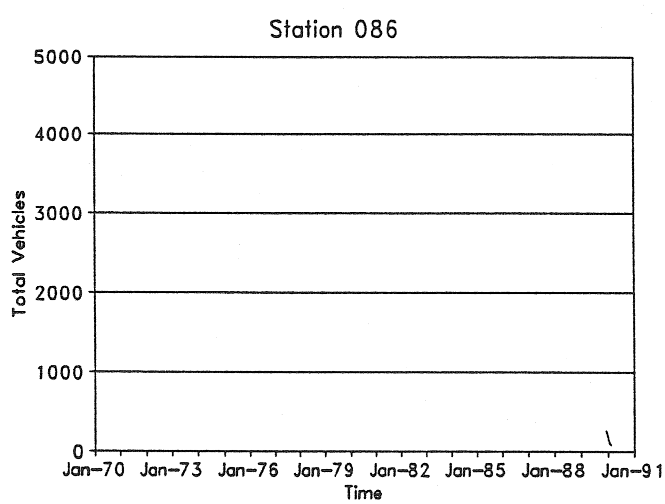


Figure 69

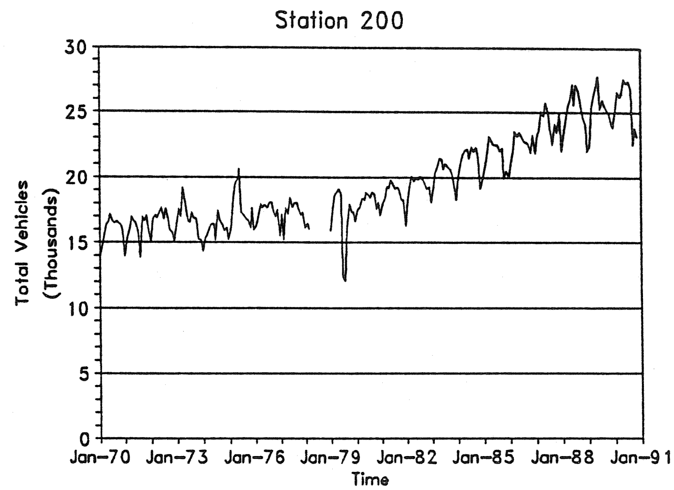


Figure 70

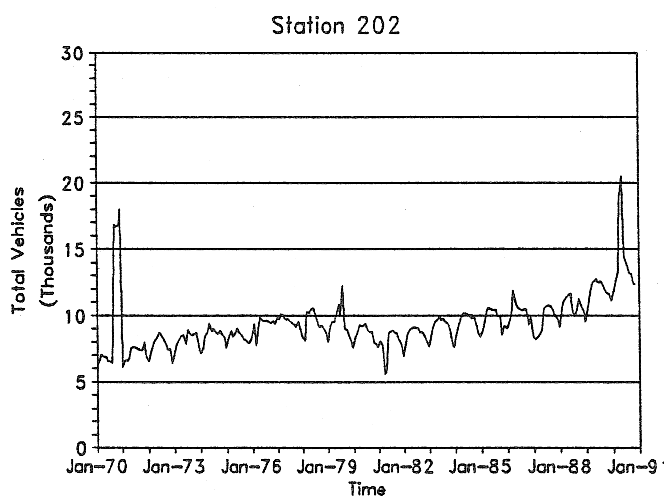


Figure 71

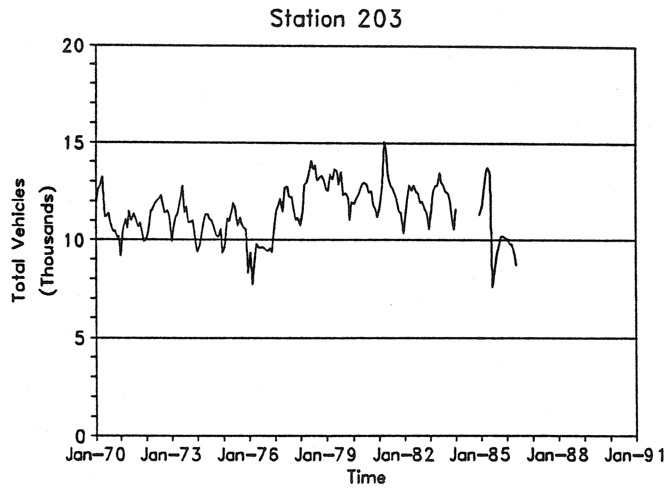

Station 203
Total Vehicles (Thousands)
20
15
10
5
0
Jan-70 Jan-73 Jan-76 Jan-79 Jan-82 Jan-85 Jan-88 Jan-91
Time

Figure 72

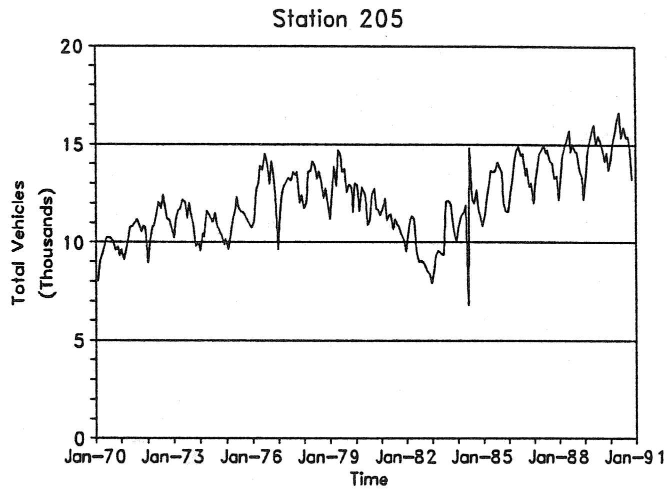


Figure 73

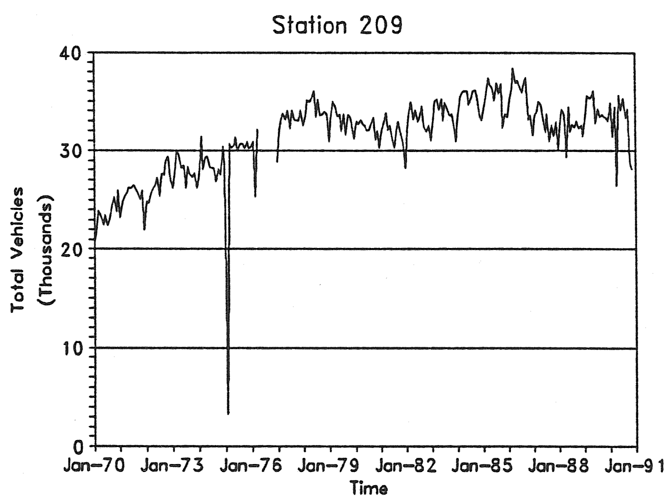


Figure 74

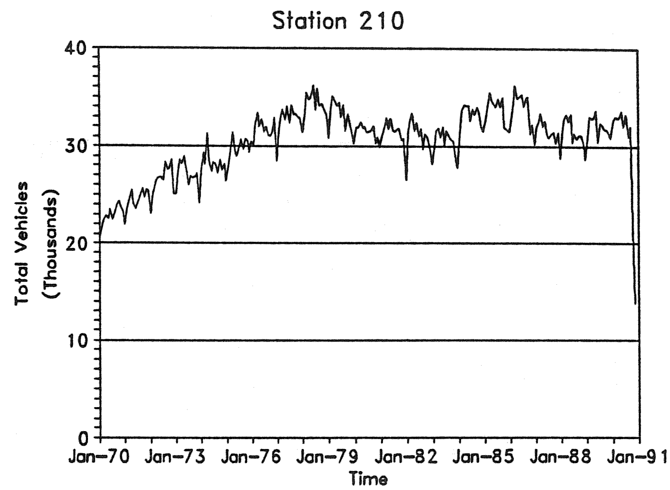


Figure 75

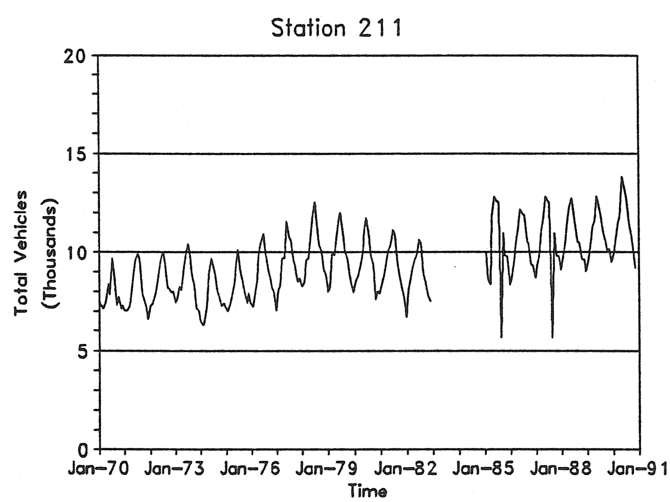


Figure 76

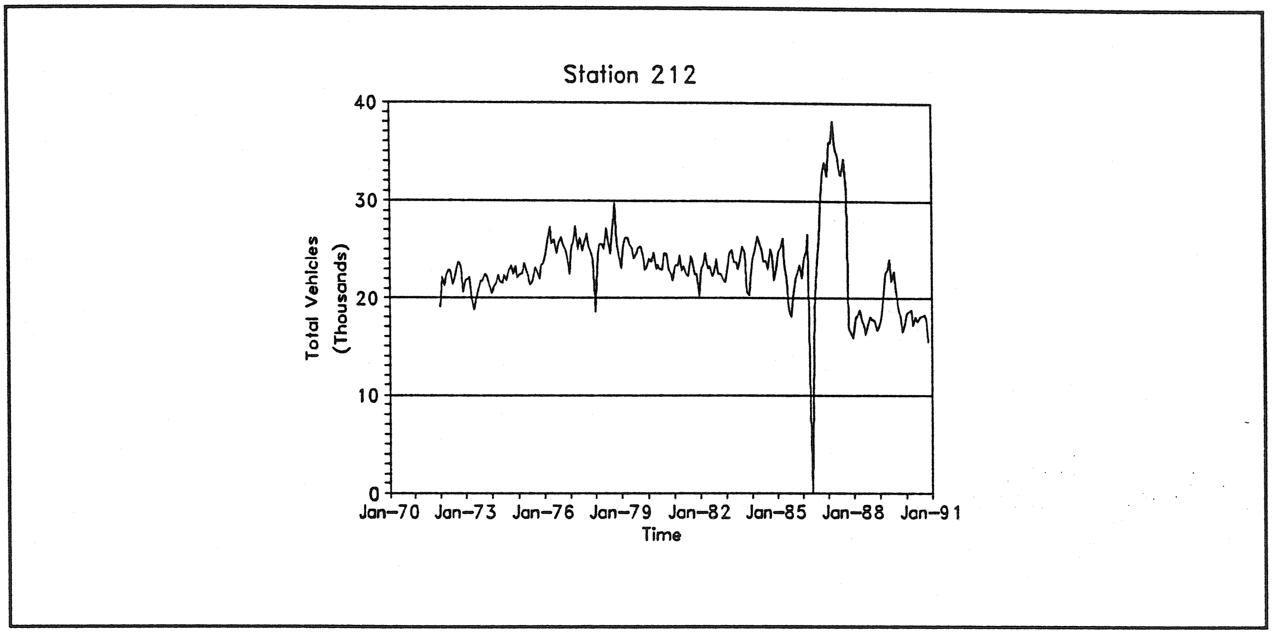
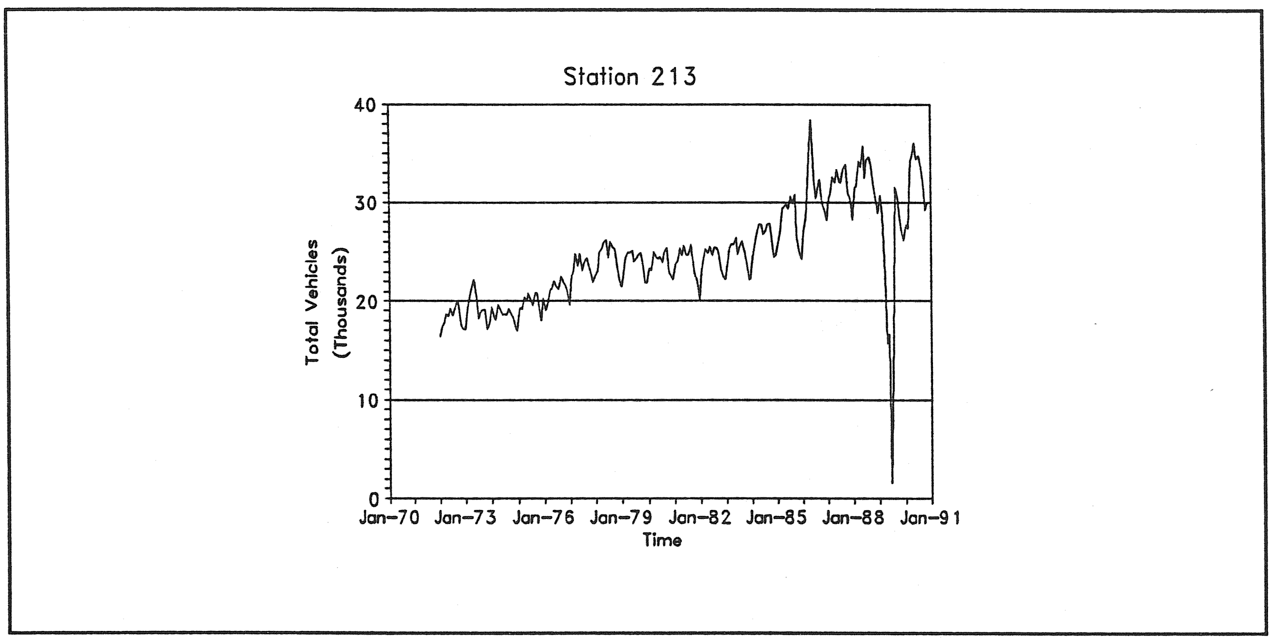


Figure 77



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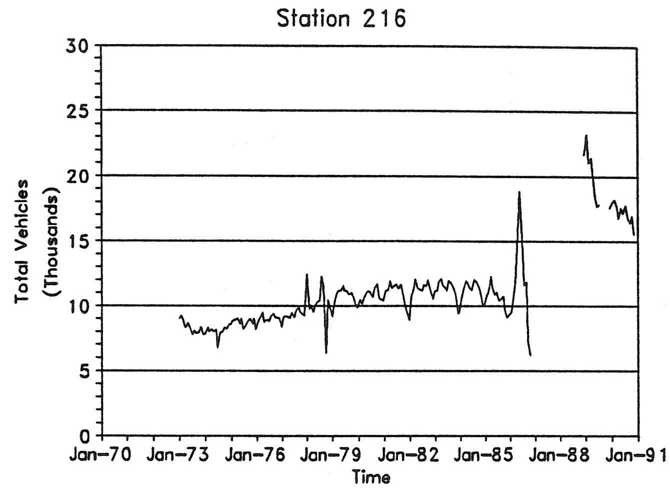

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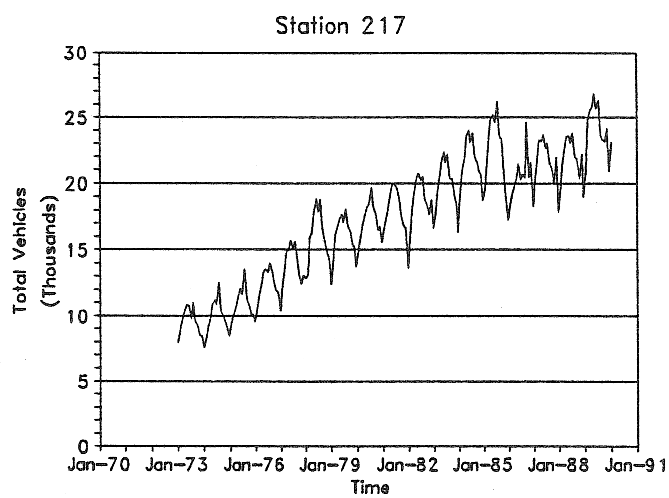

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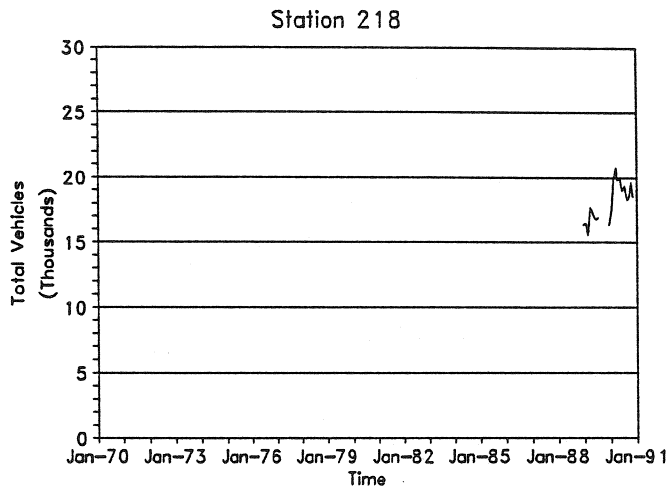

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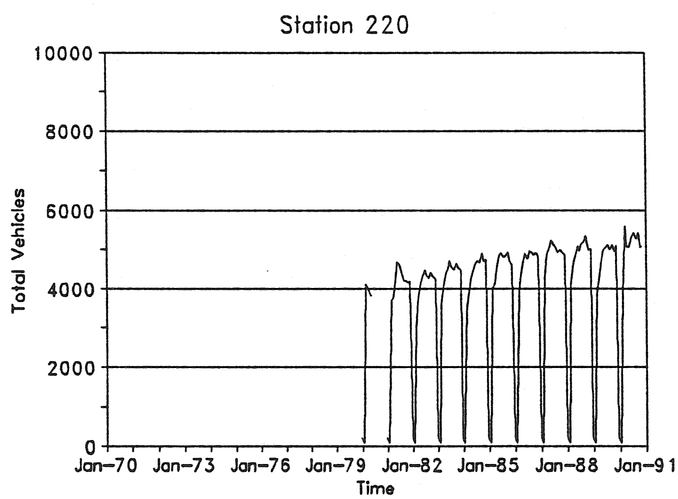

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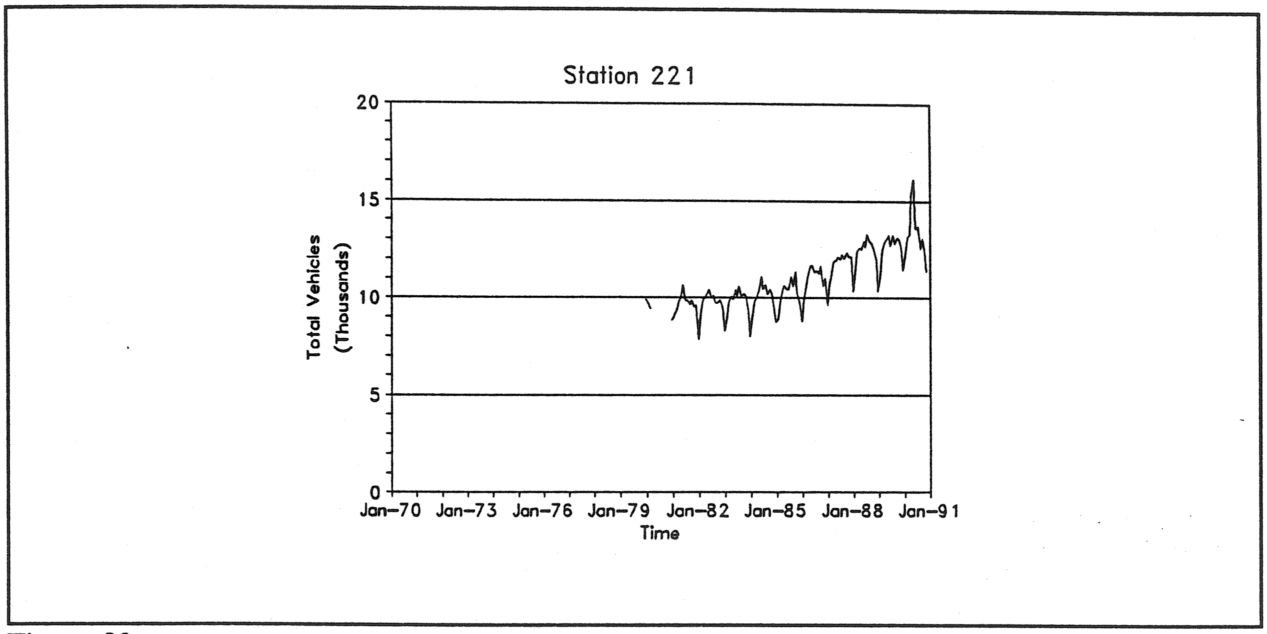

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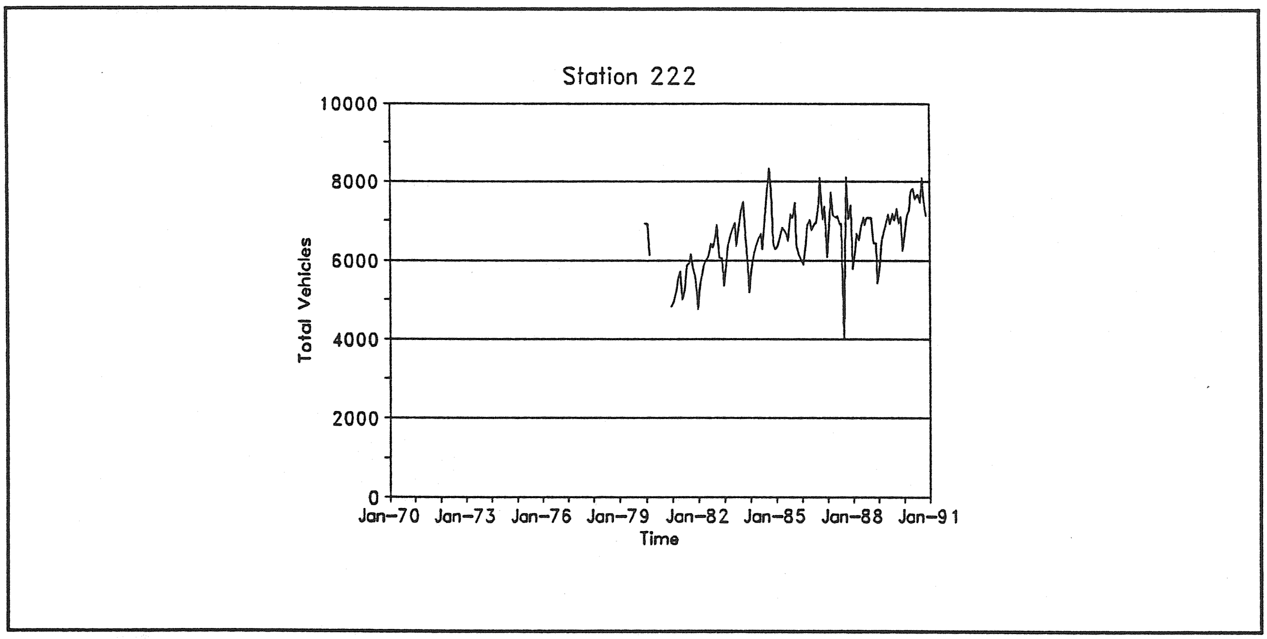

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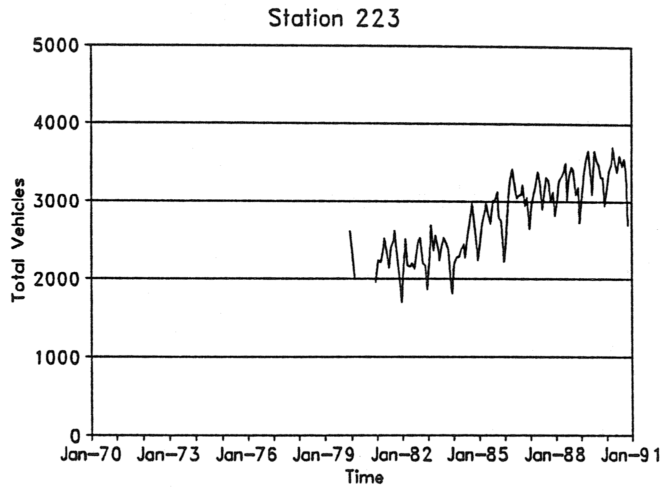

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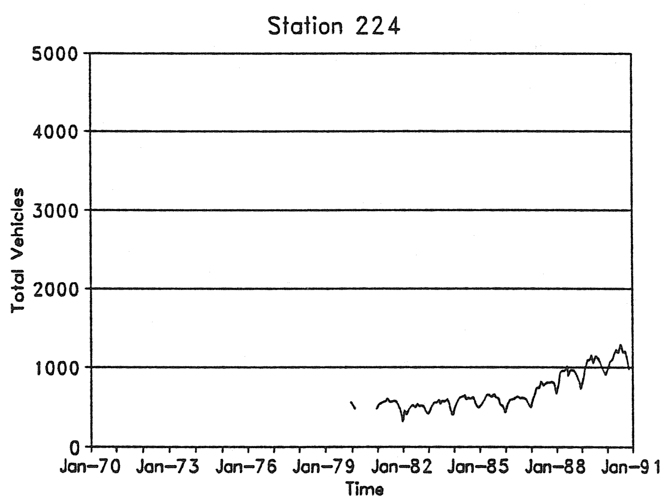
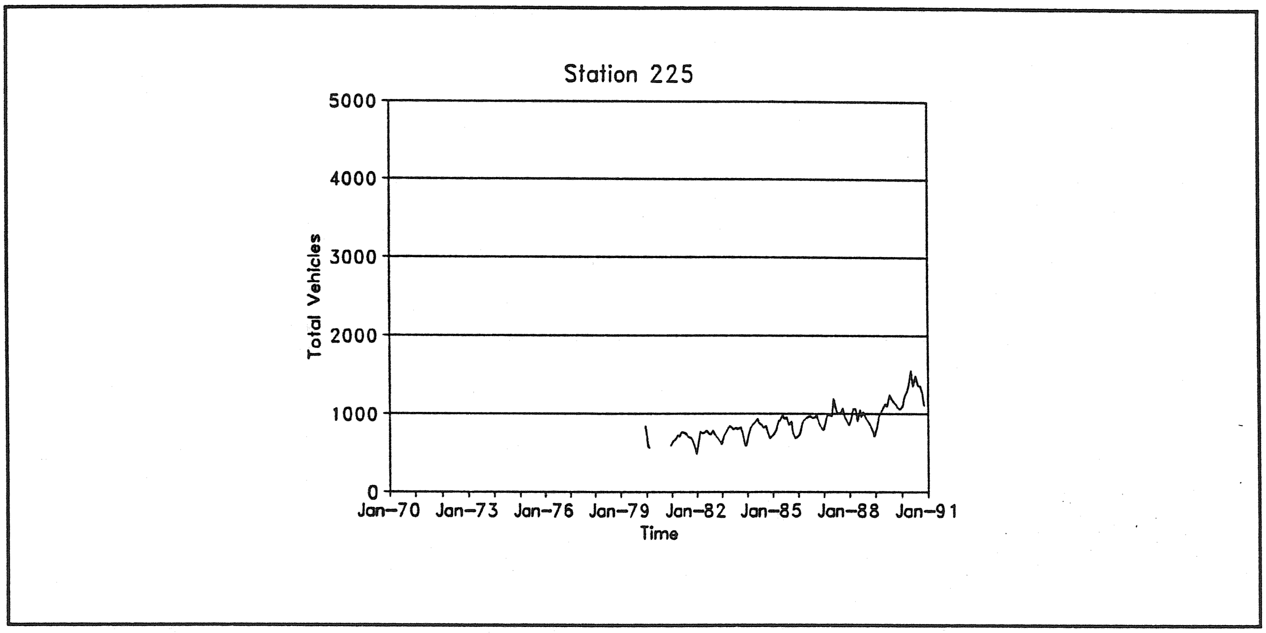


Figure 86



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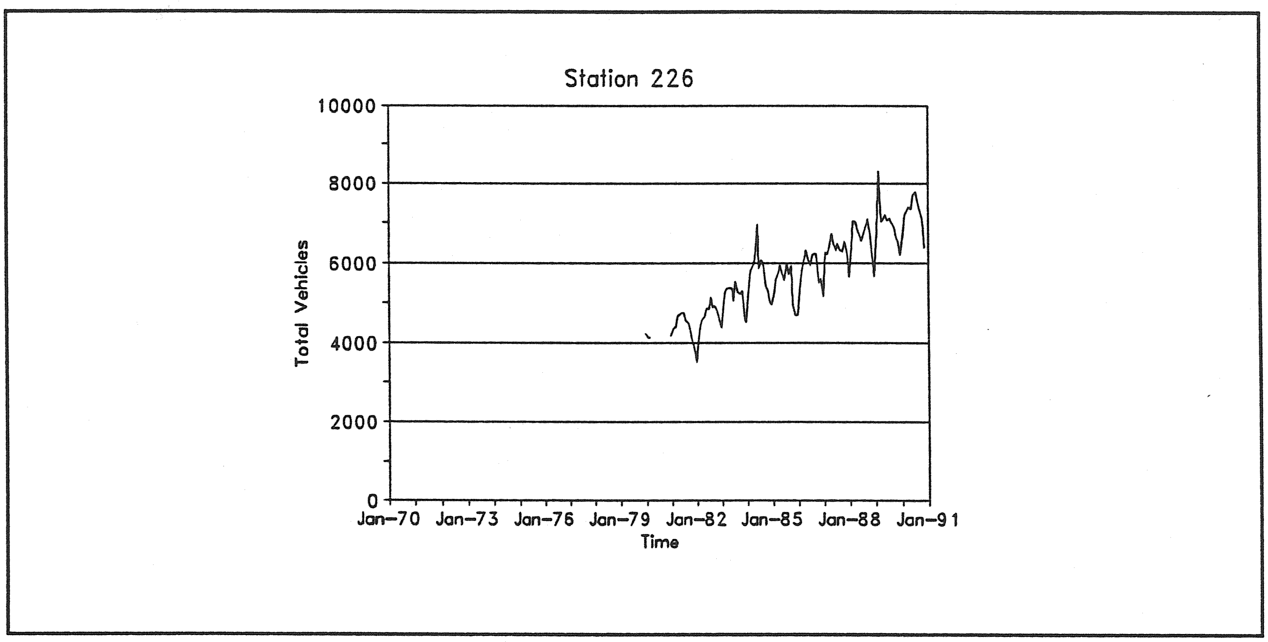

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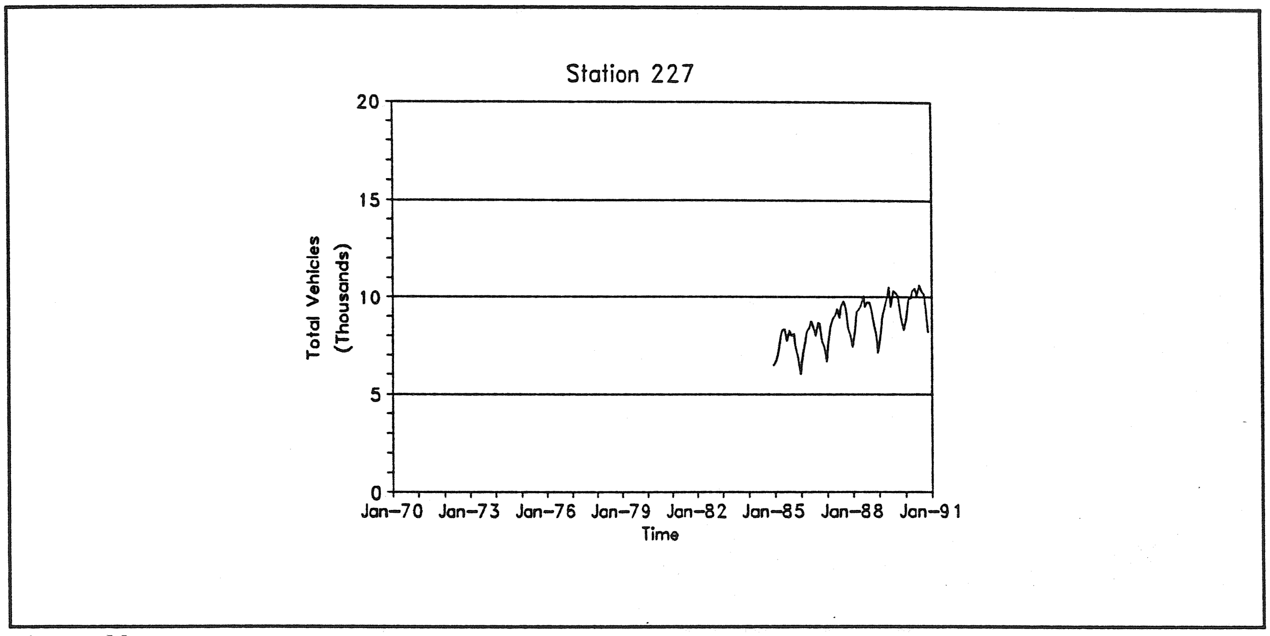

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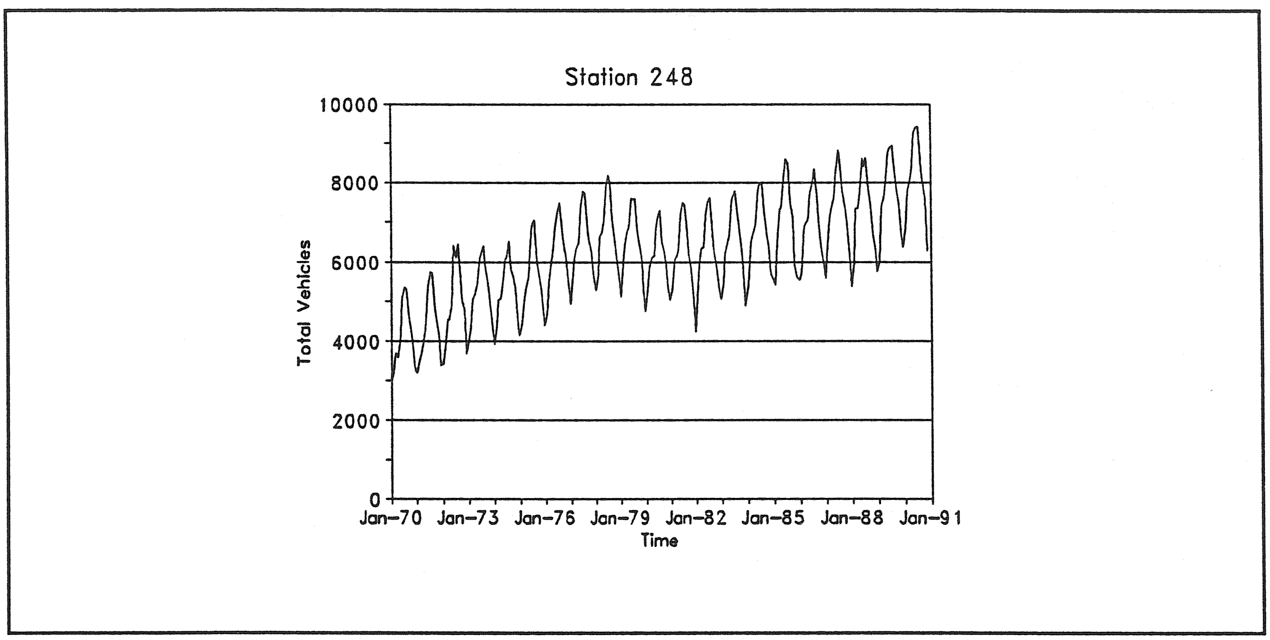


Figure 90

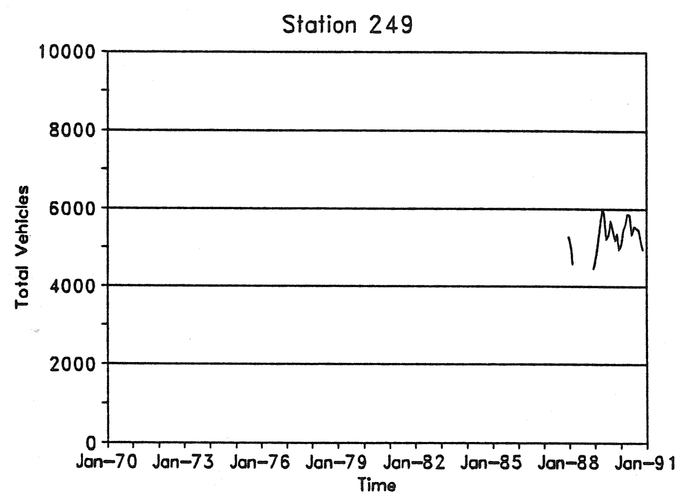


Figure 91

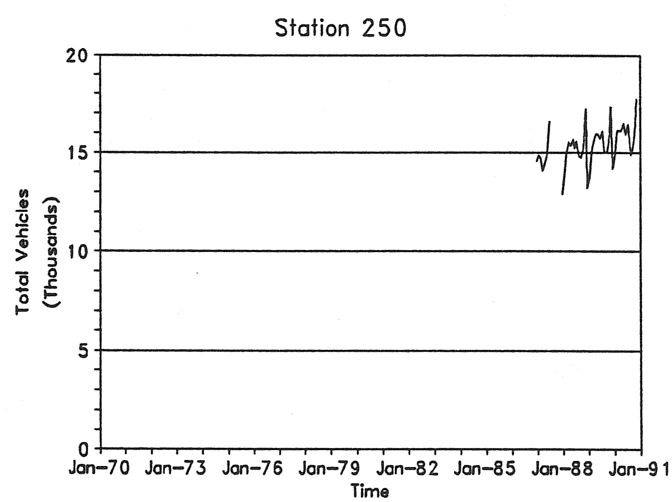


Figure 92

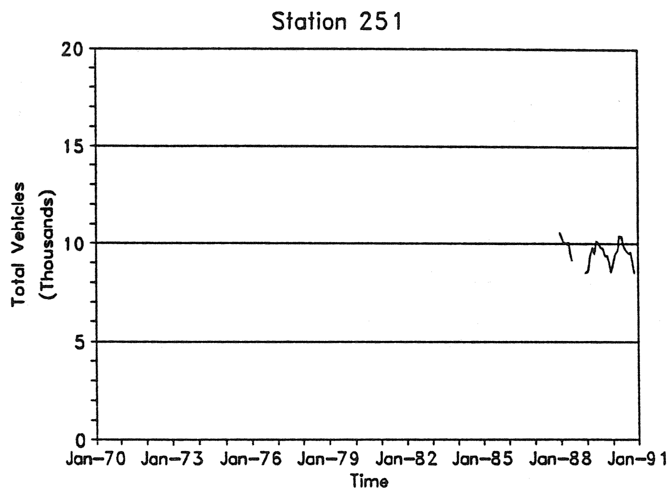


Figure 93

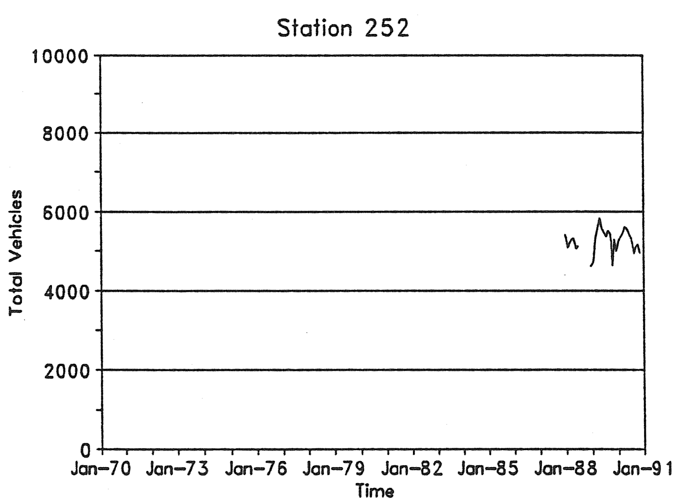


Figure 94

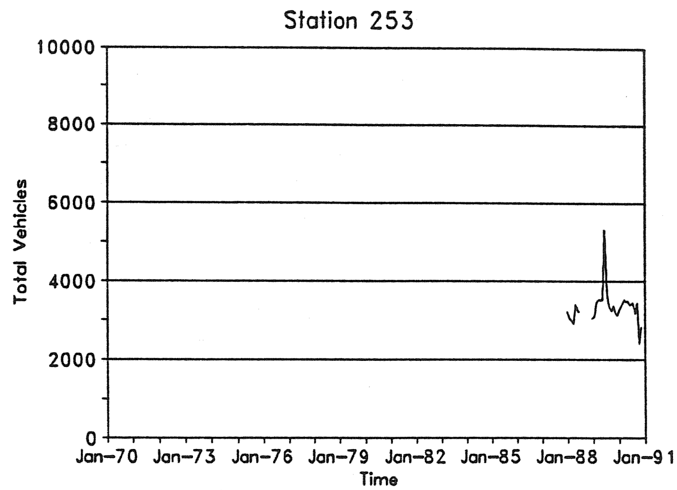
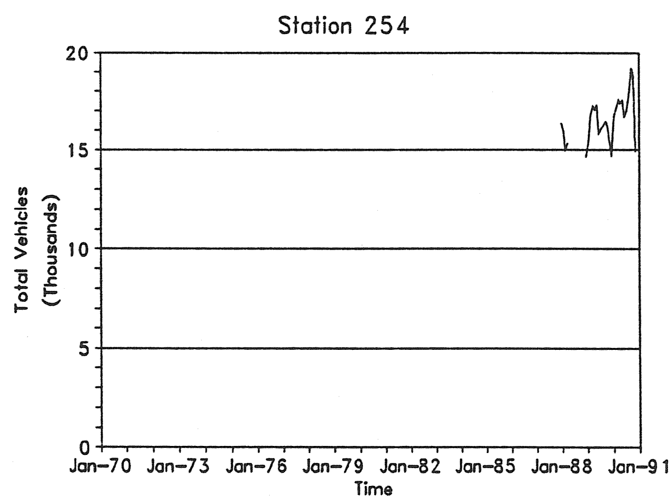


Figure 95



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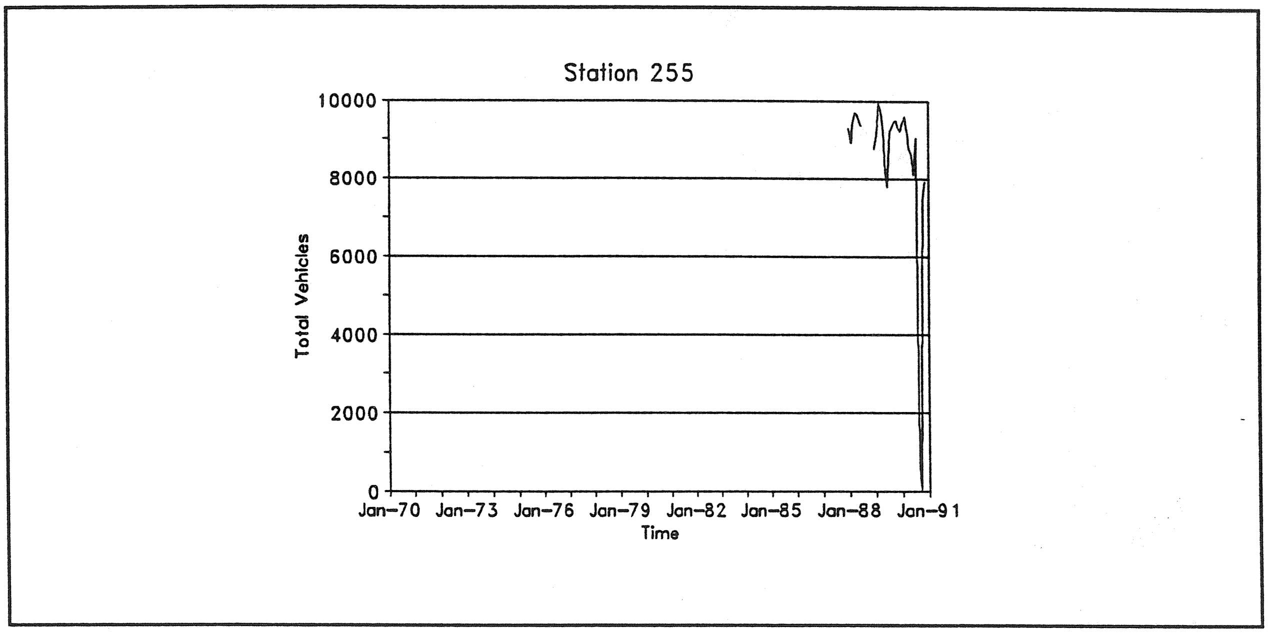
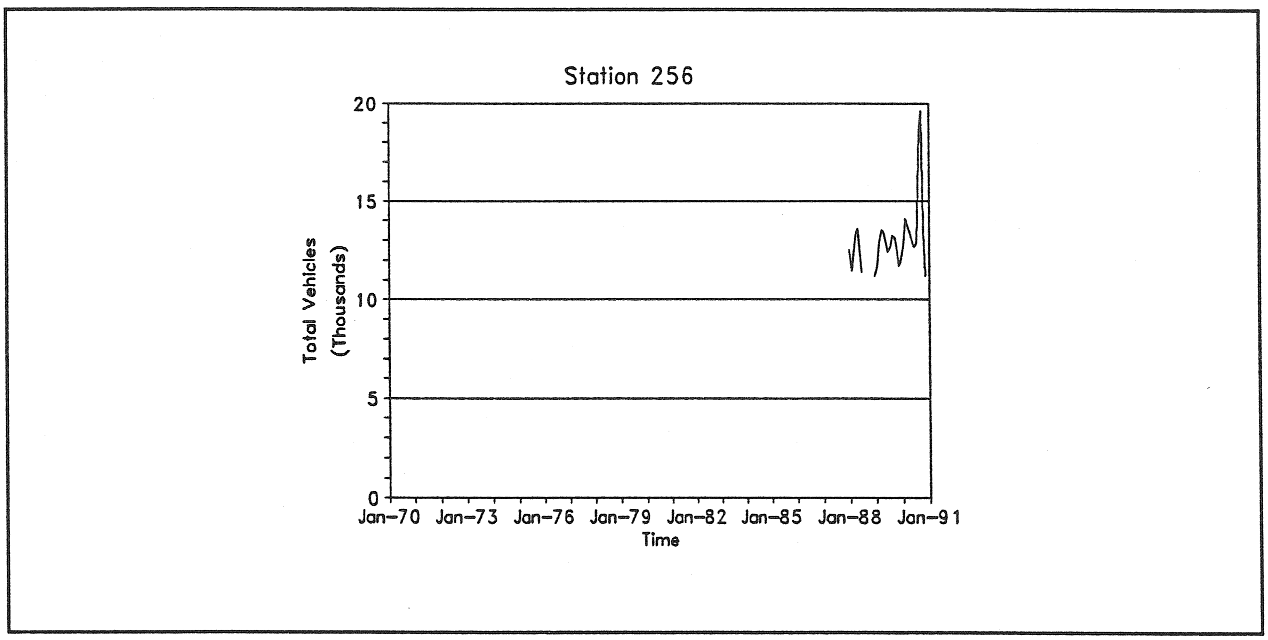


Figure 97



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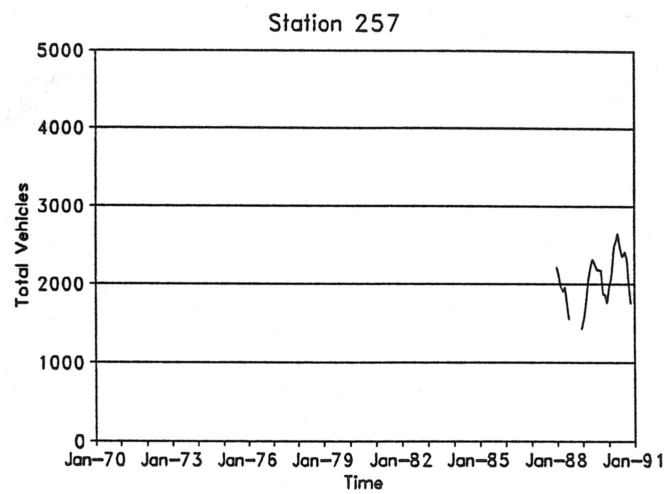

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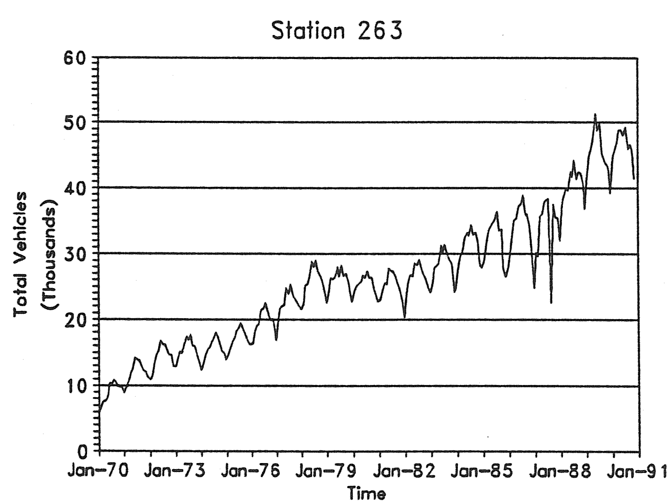


Figure 100

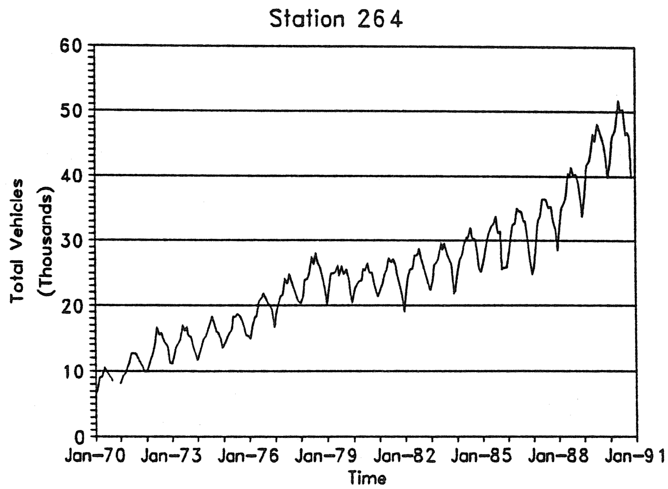


Figure 101

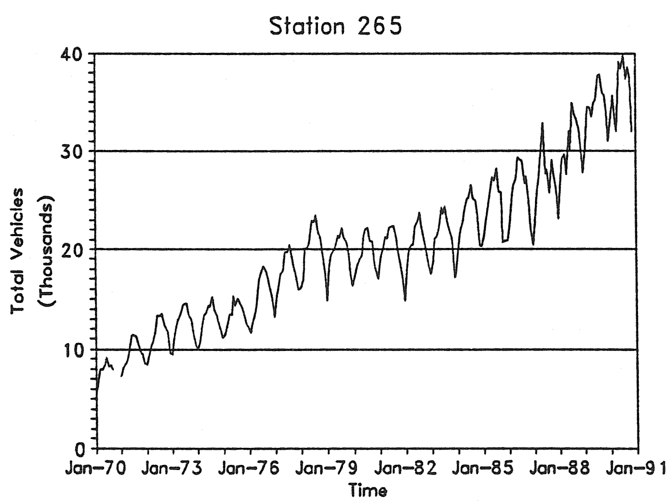


Figure 102

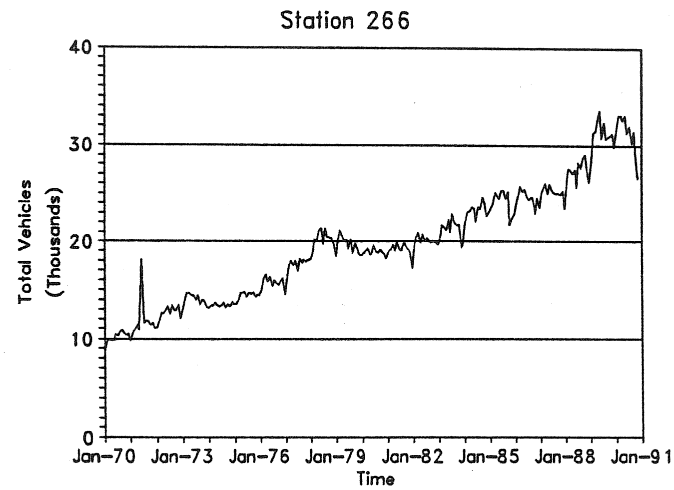


Figure 103

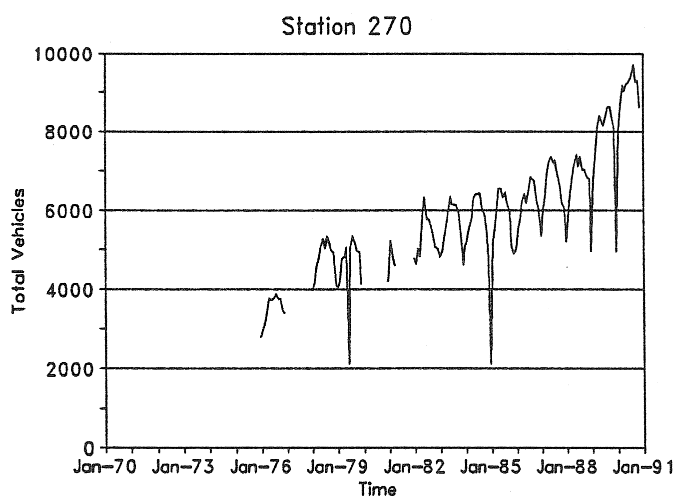
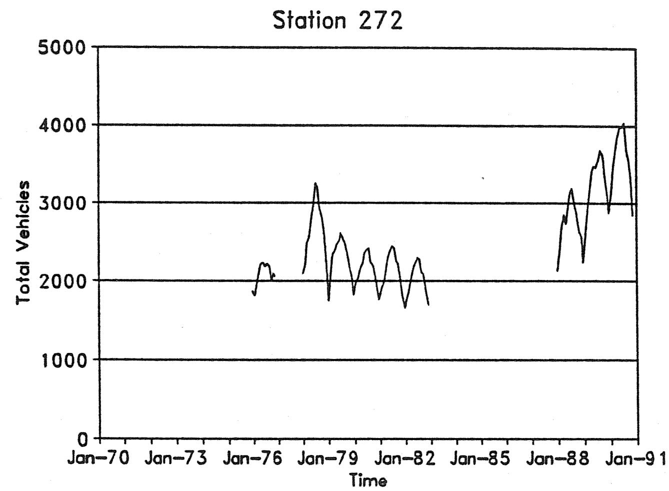


Figure 104



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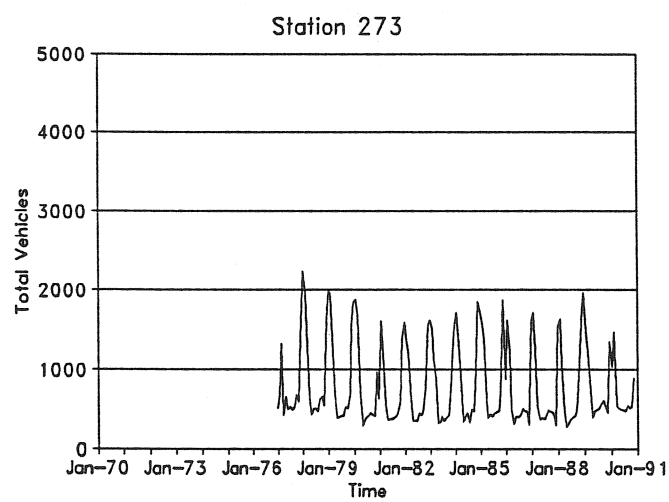


Figure 106

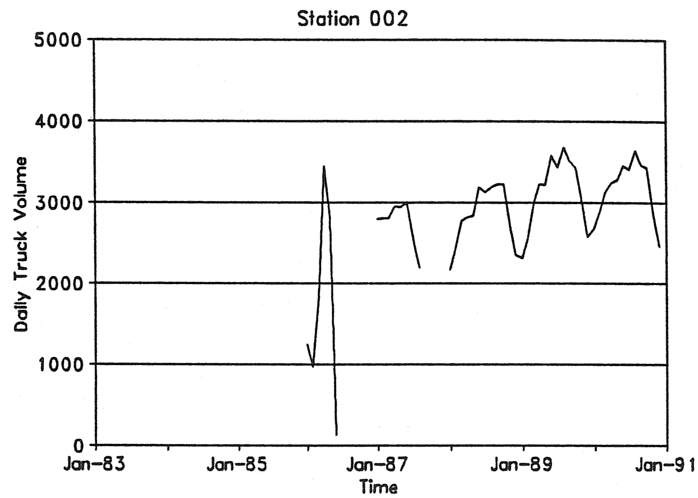


Figure 1

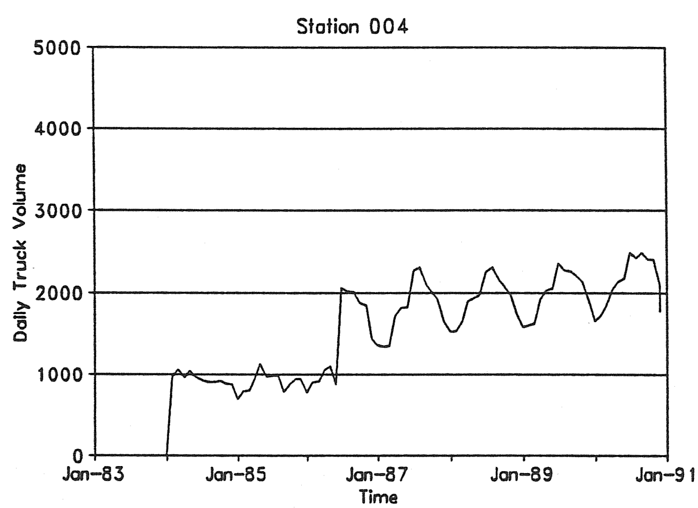


Figure 2

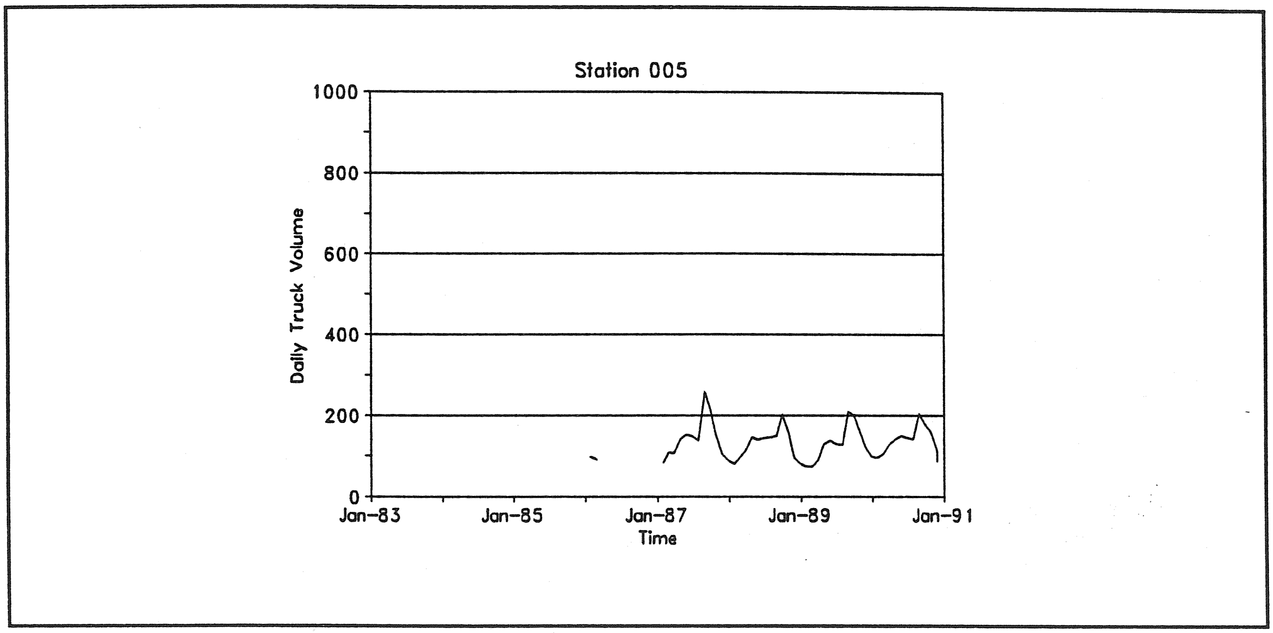


Figure 3

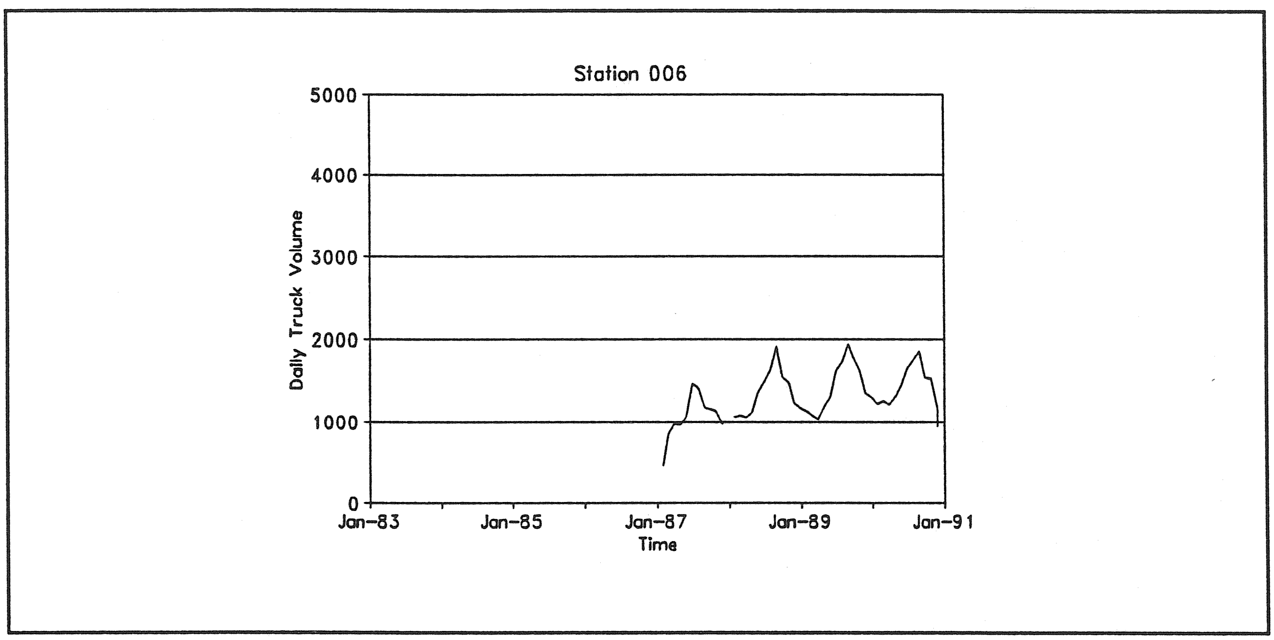


Figure 4

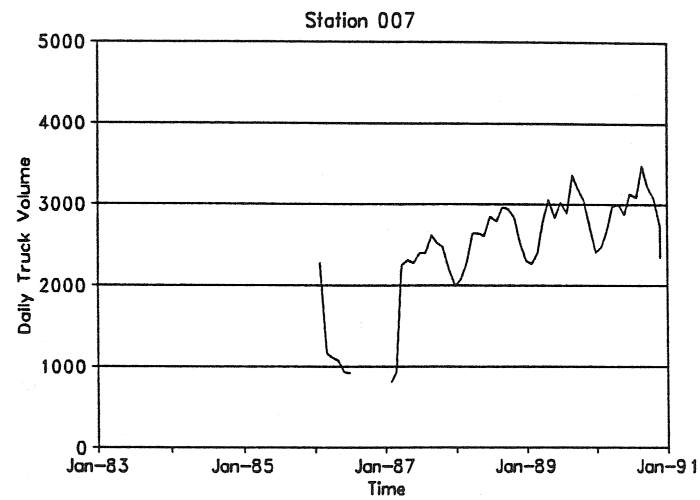


Figure 5

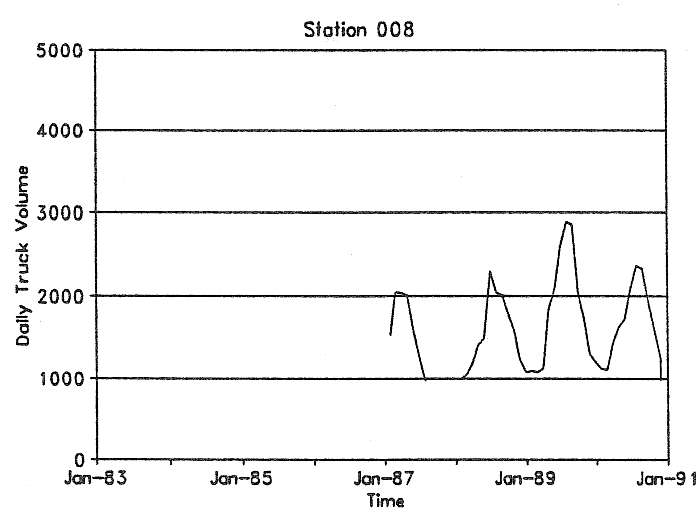


Figure 6

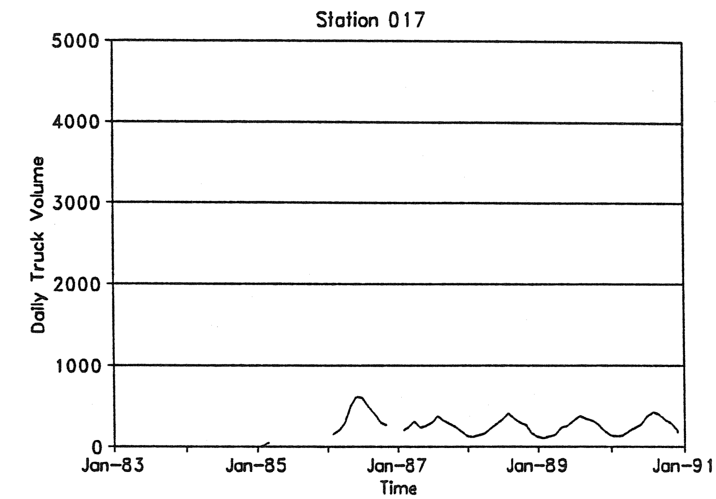


Figure 7

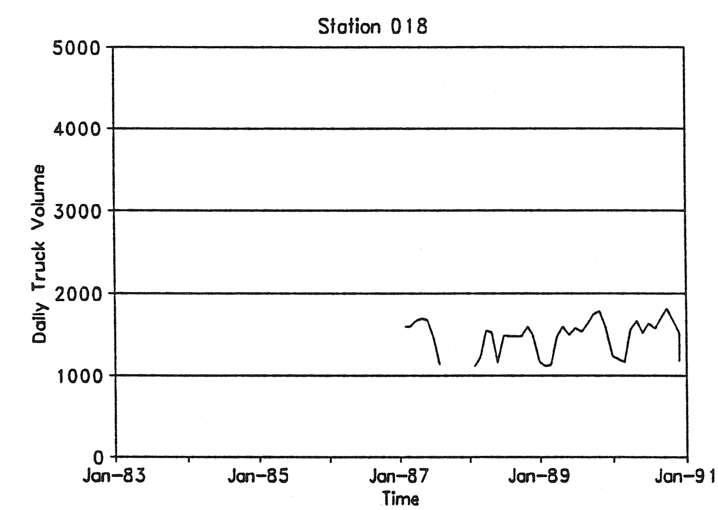


Figure 8

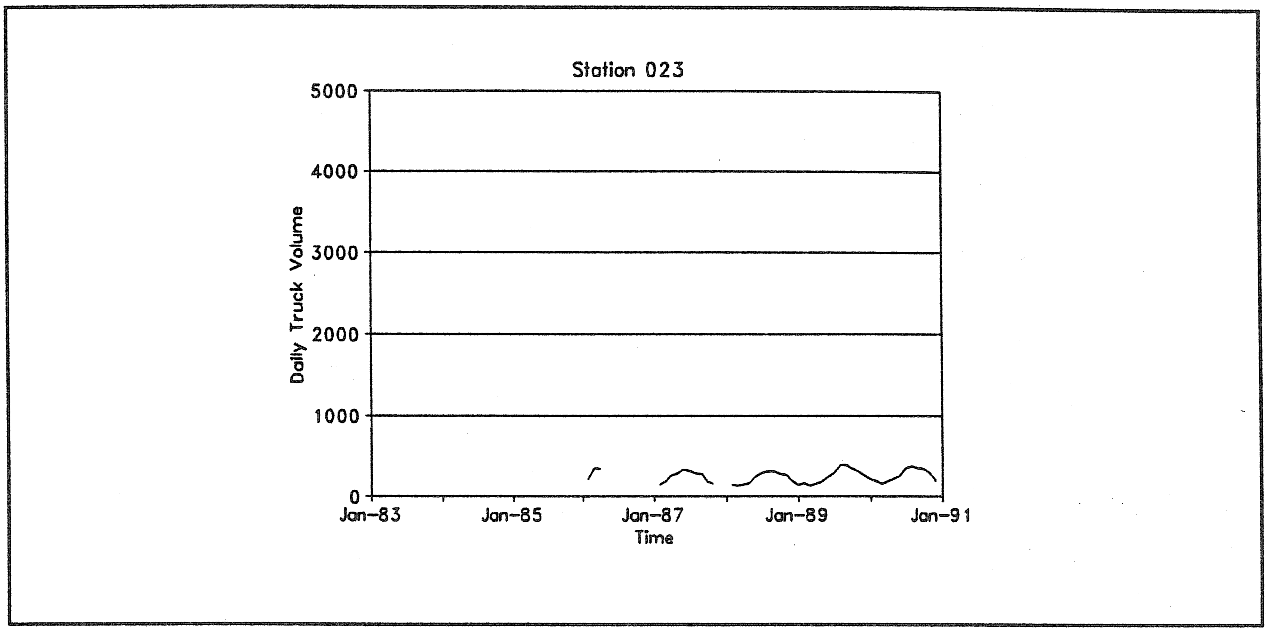


Figure 9

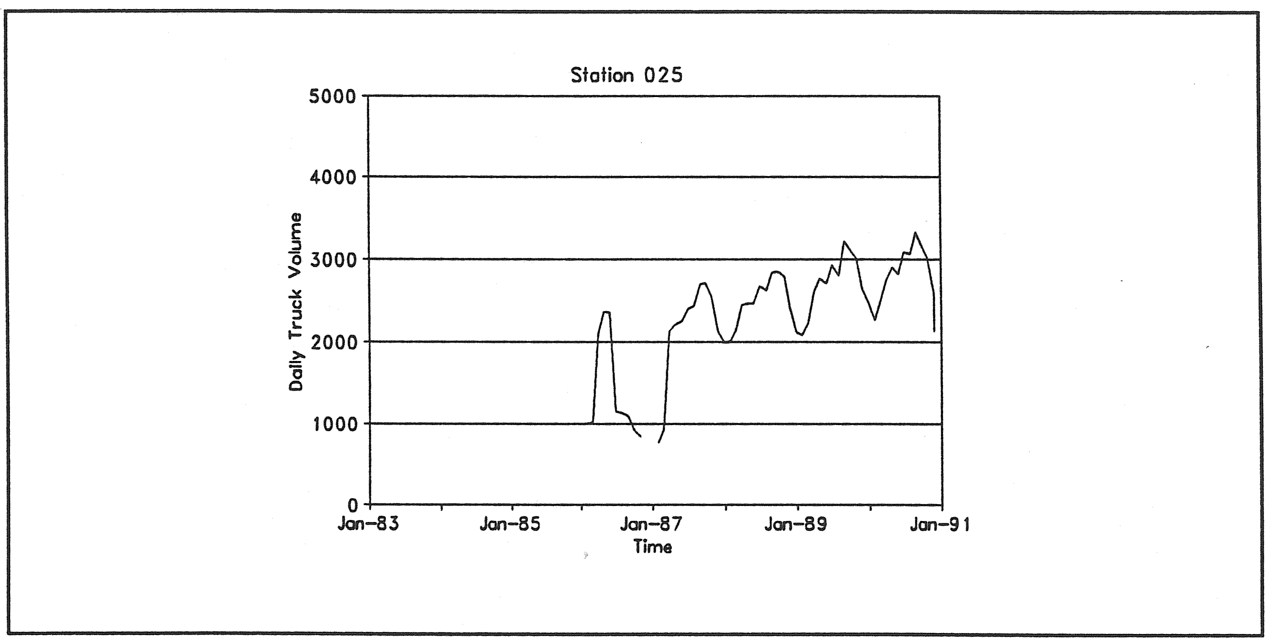


Figure 10

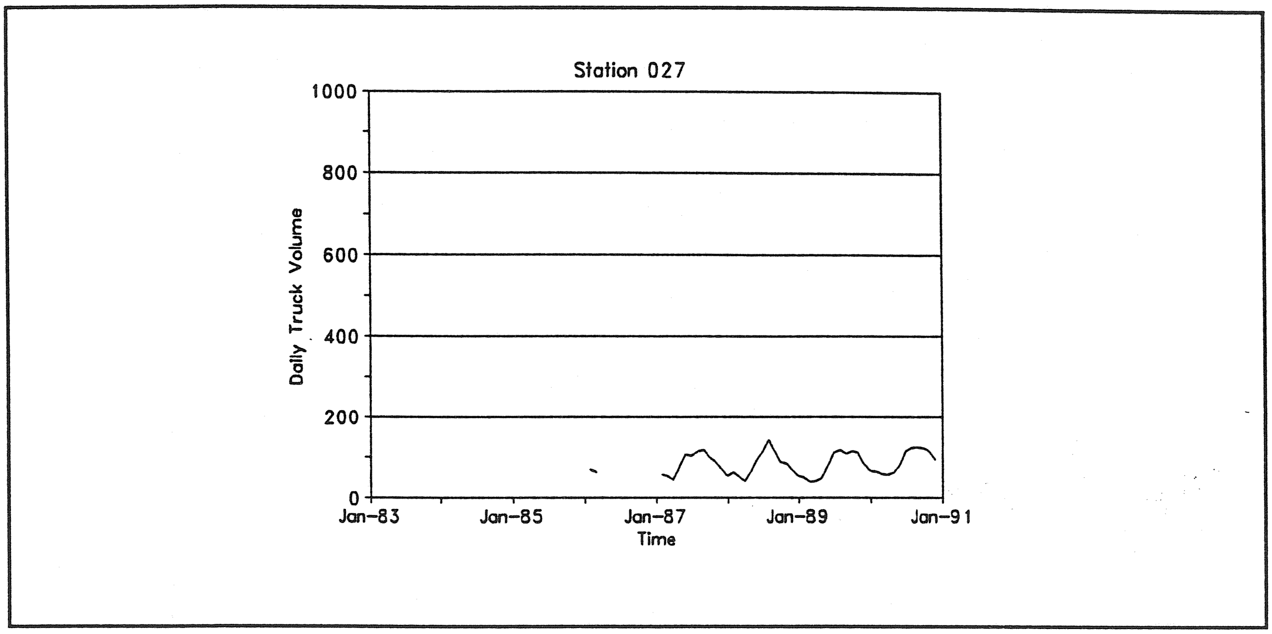
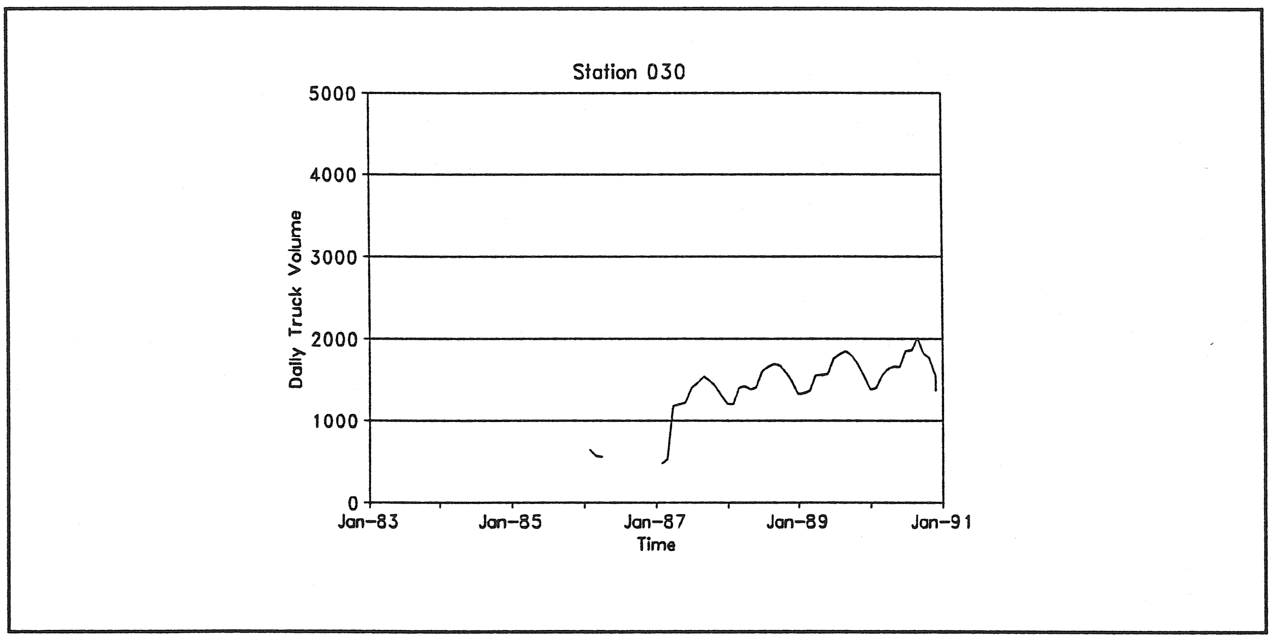


Figure 11



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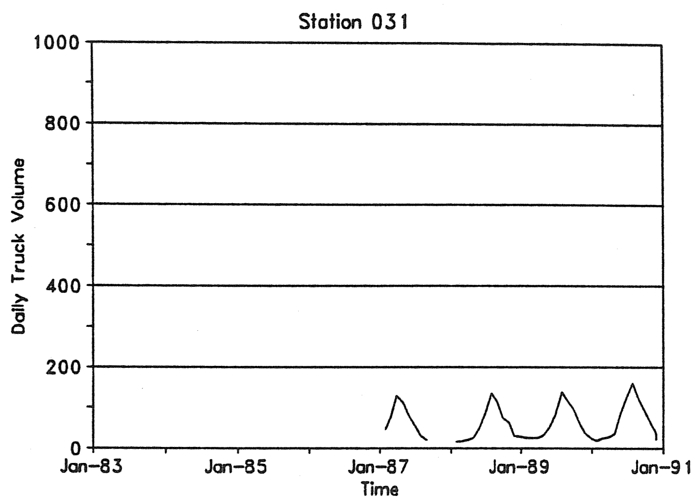


Figure 13

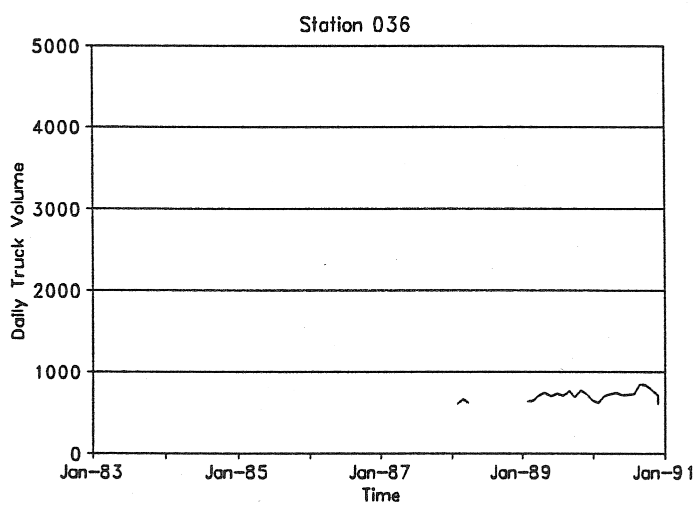


Figure 14

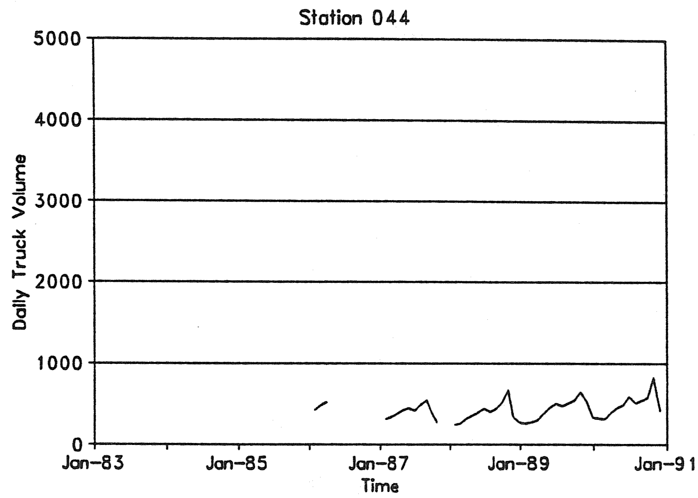


Figure 15

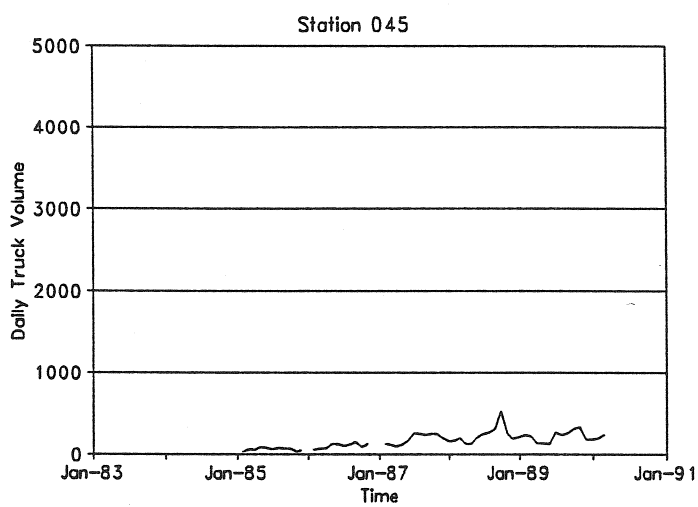


Figure 16

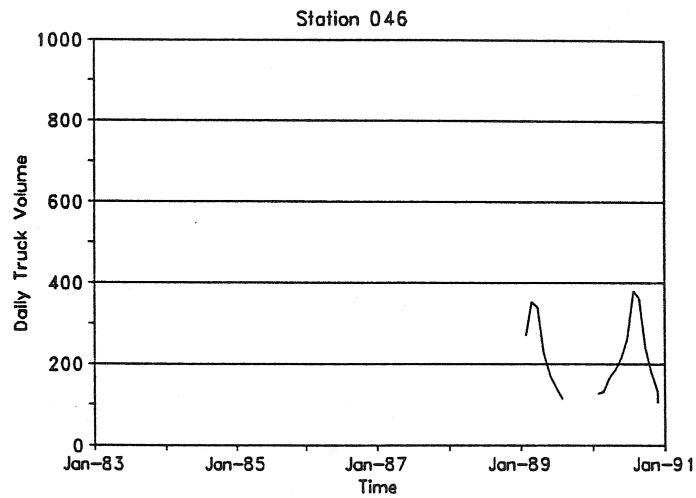


Figure 17

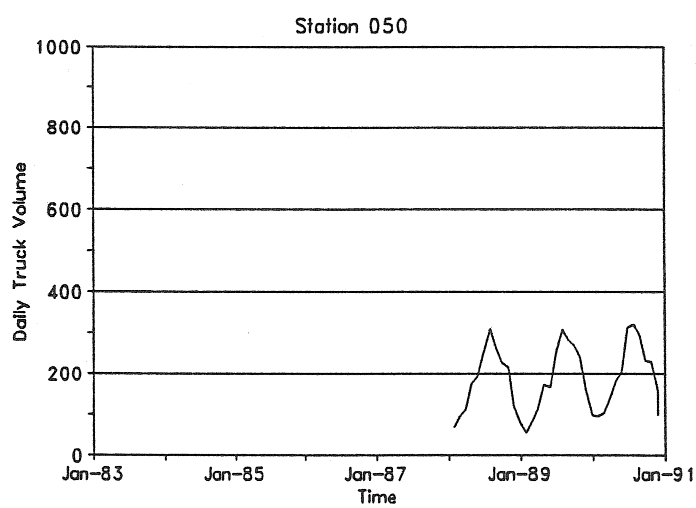


Figure 18

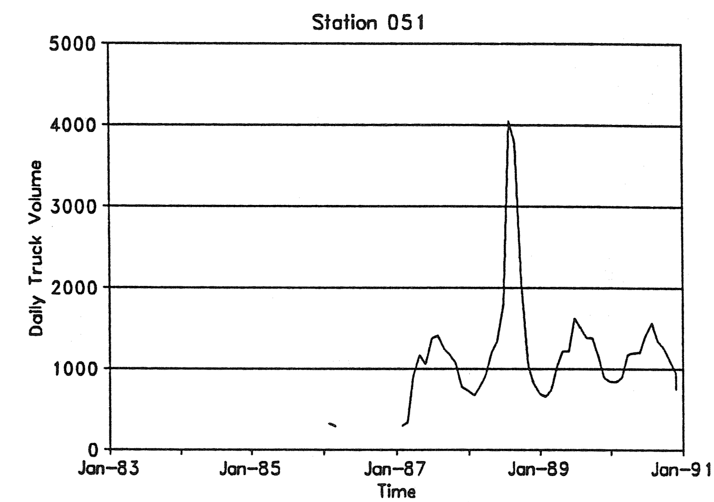


Figure 19

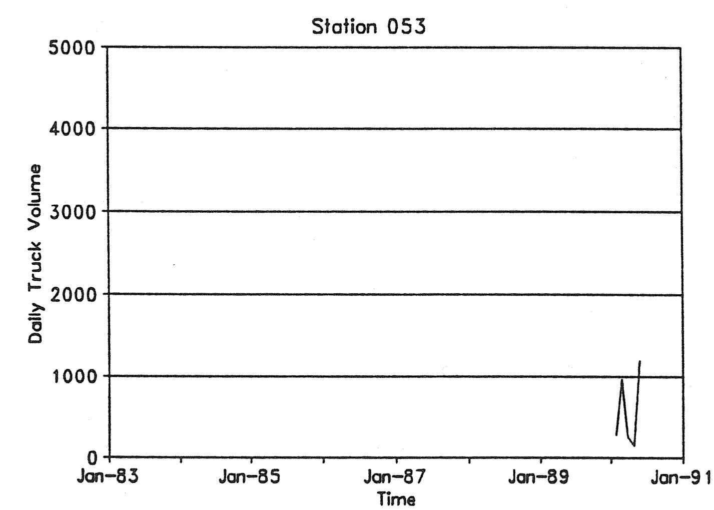


Figure 20

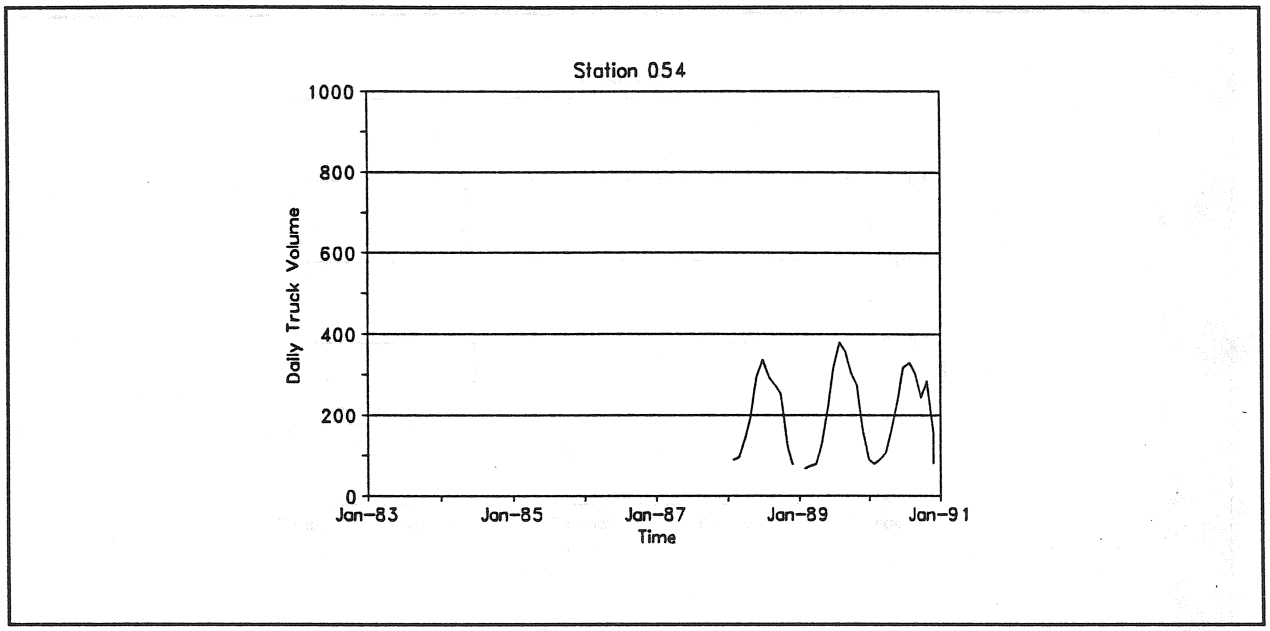
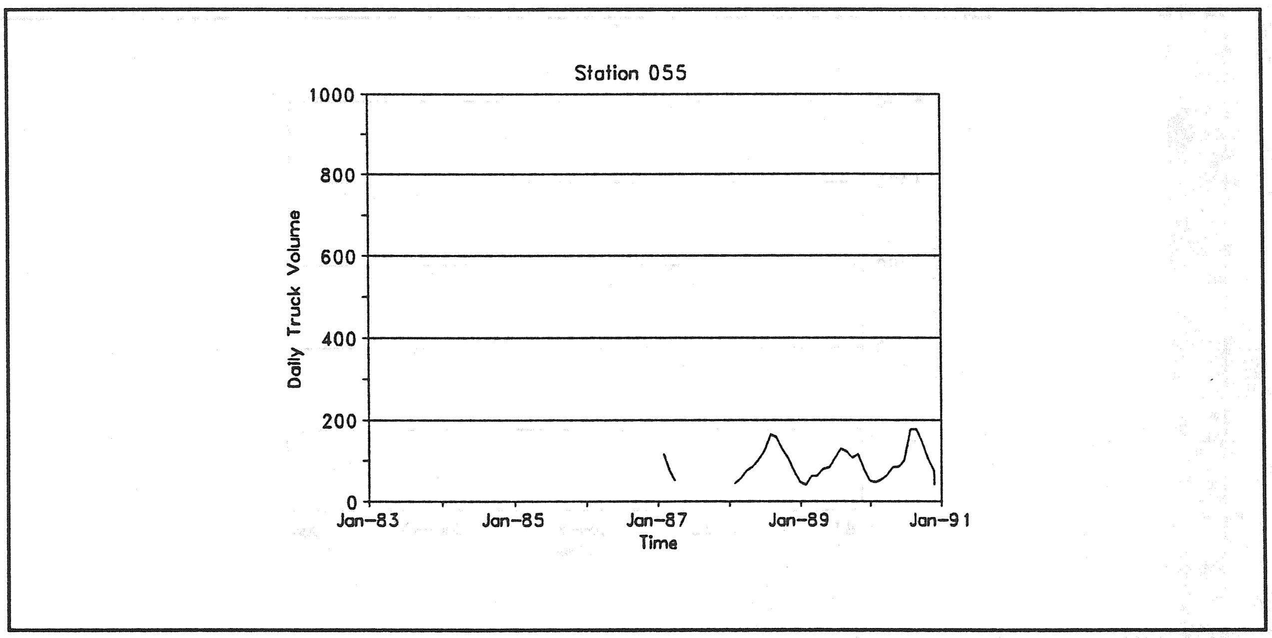


Figure 21



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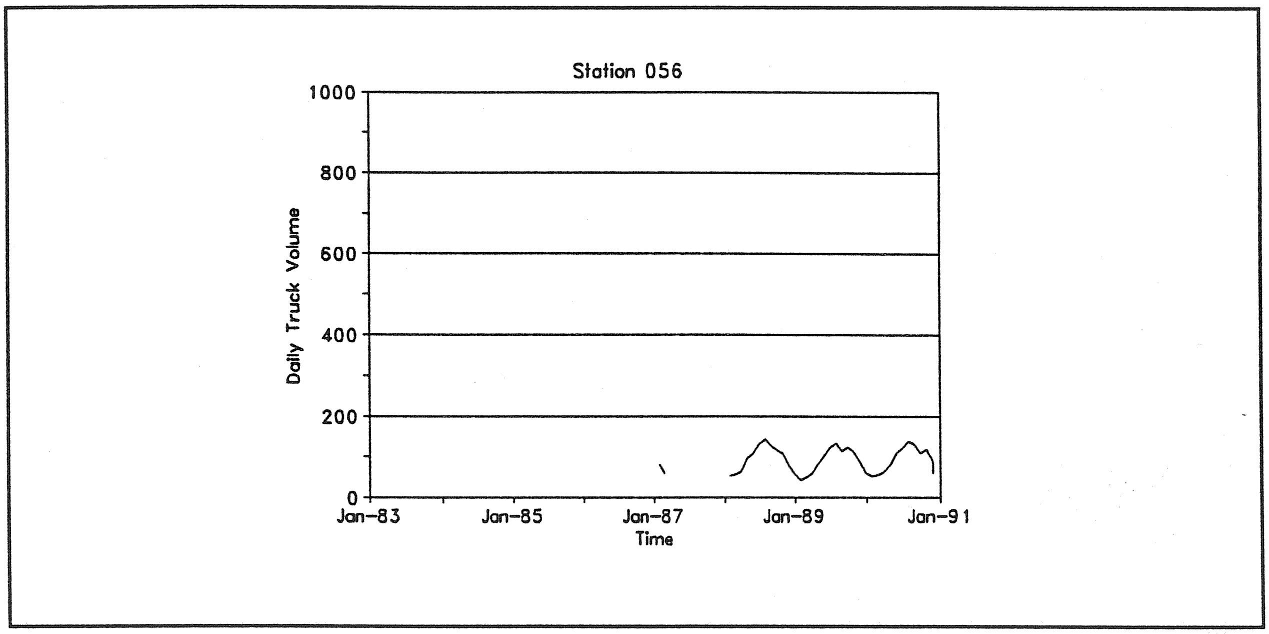

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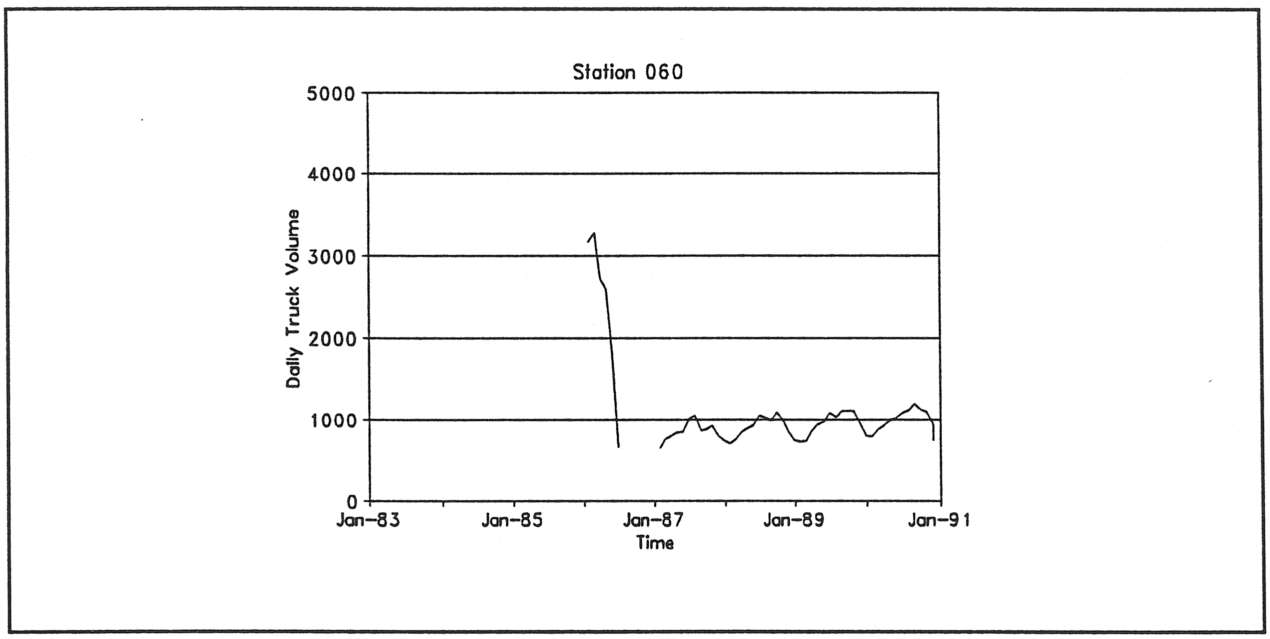

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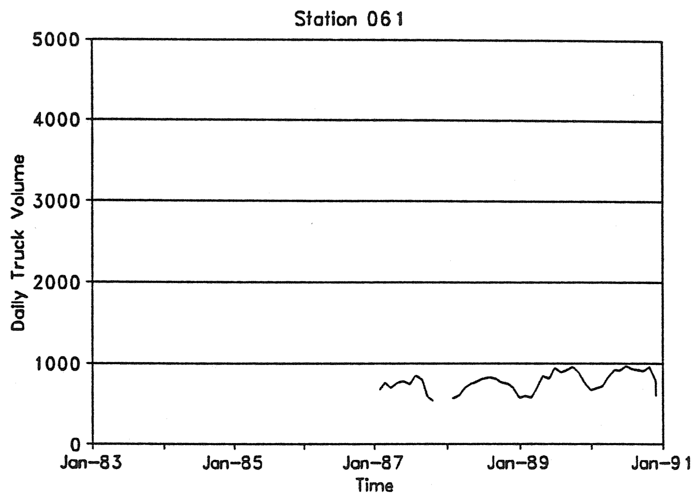

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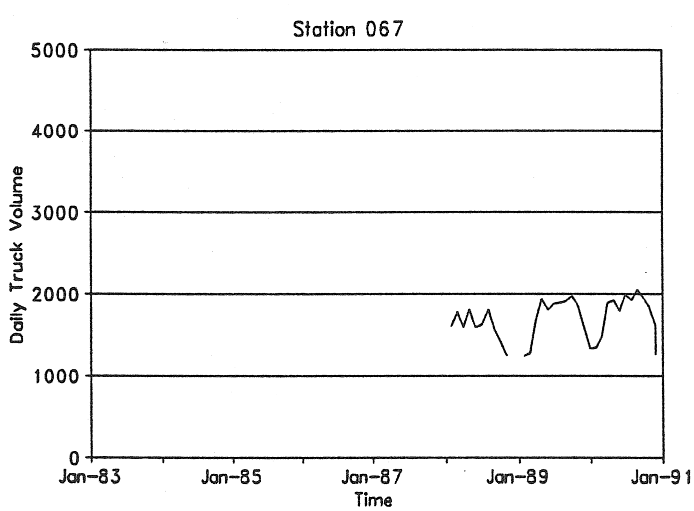

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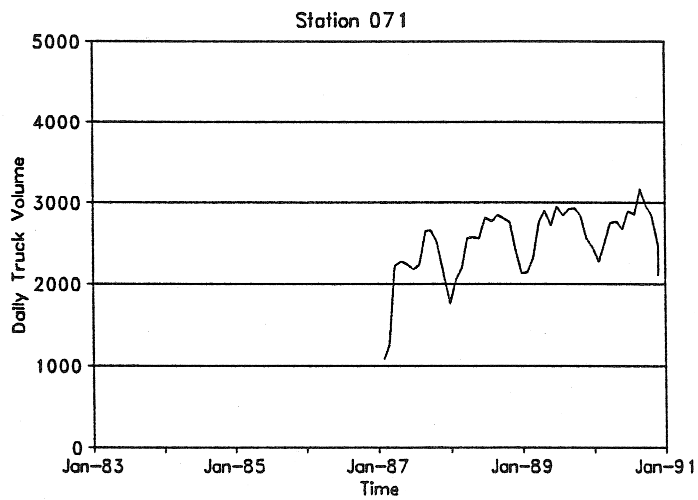

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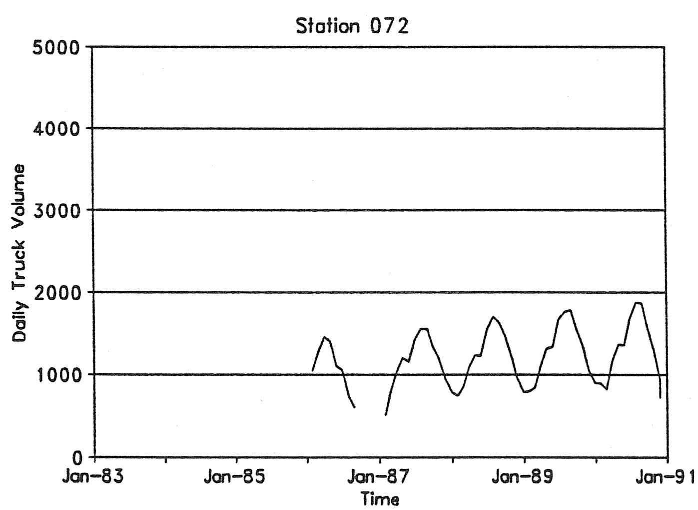

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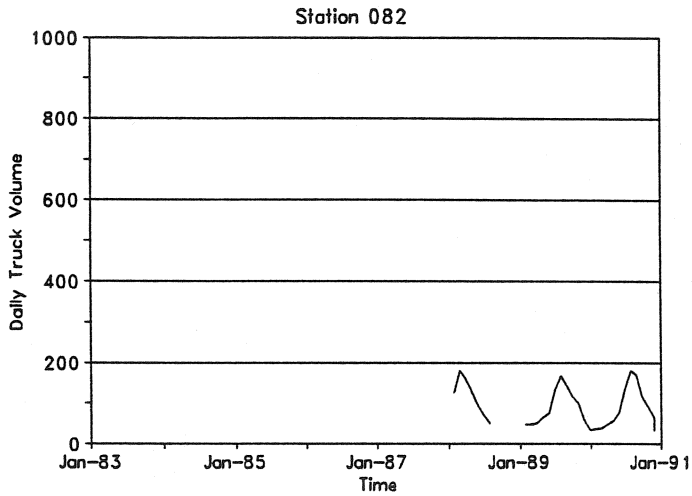

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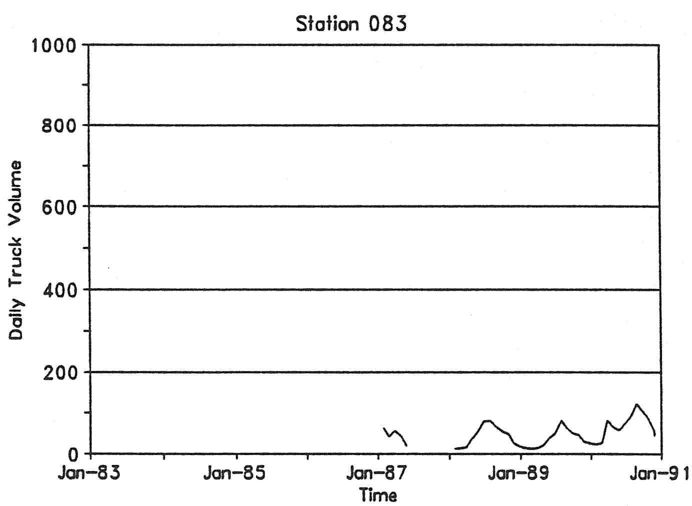

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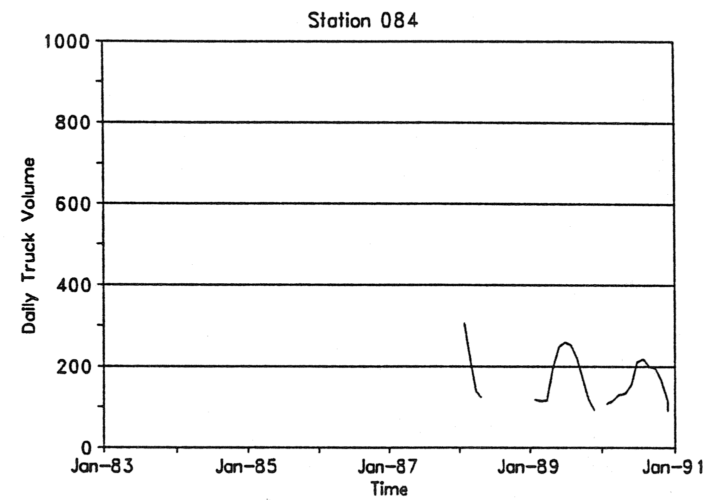

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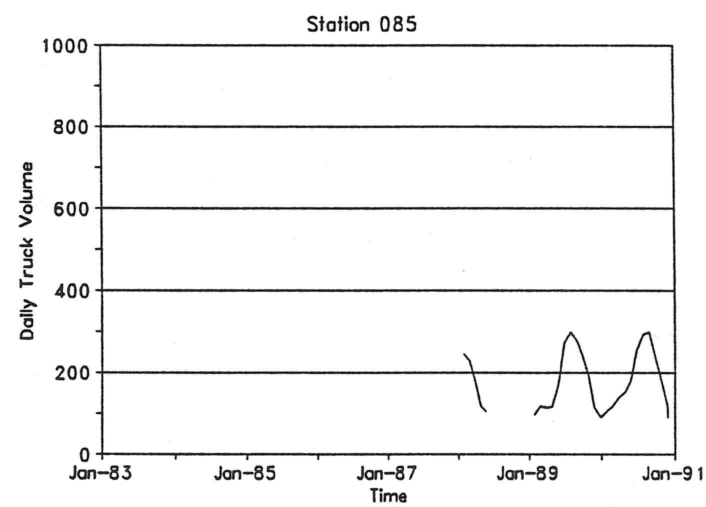

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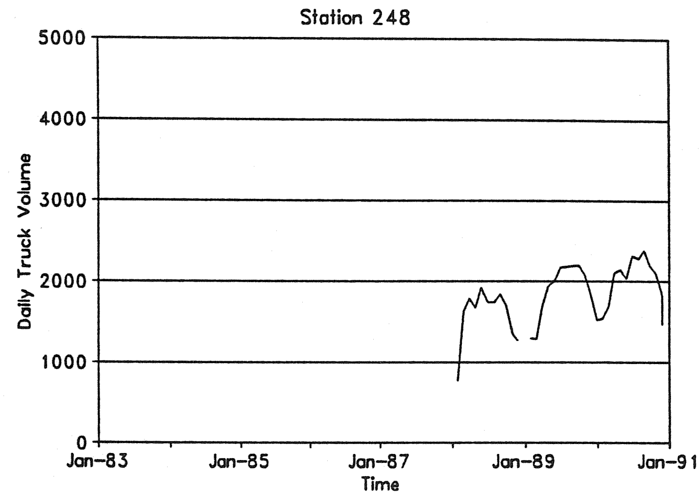

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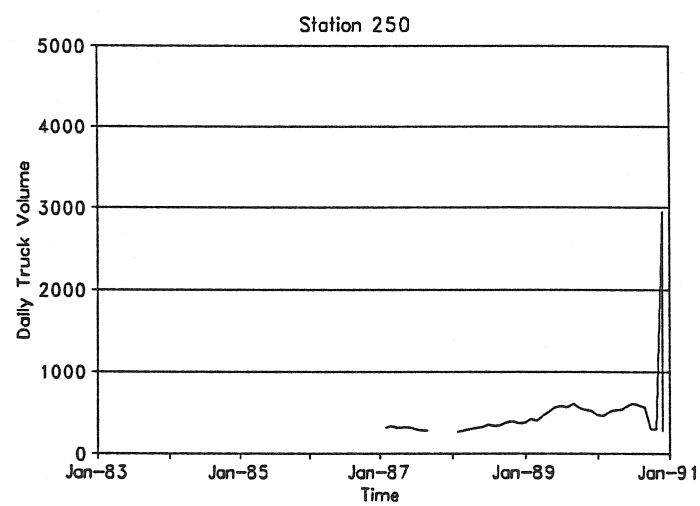

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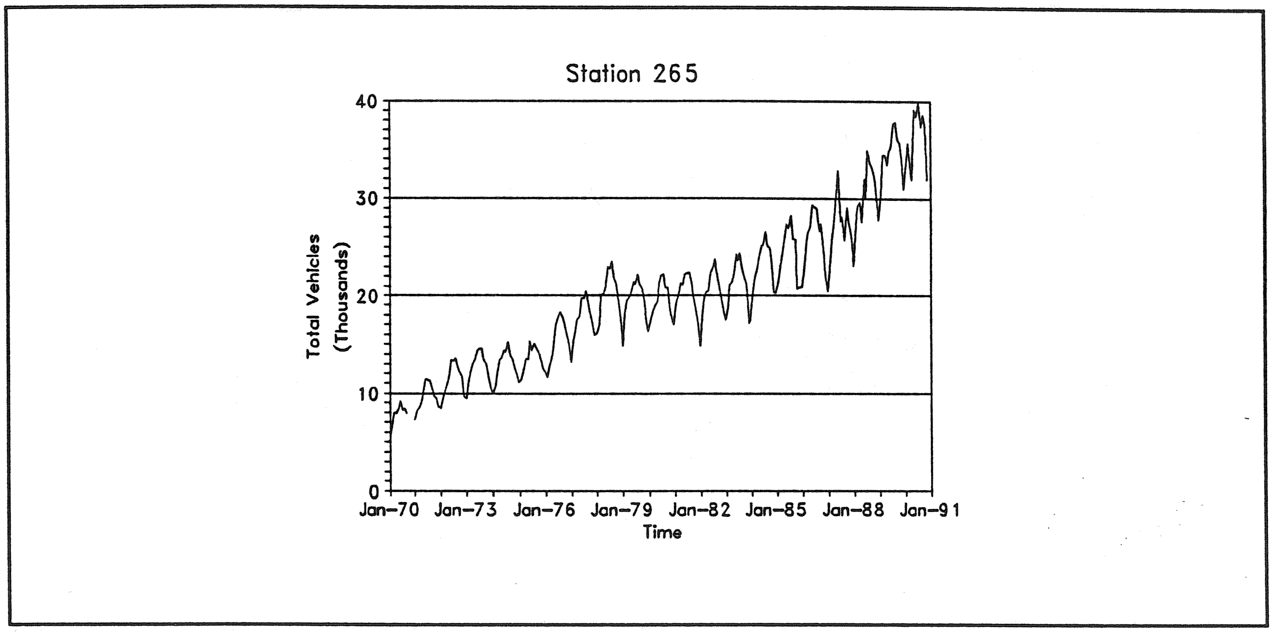

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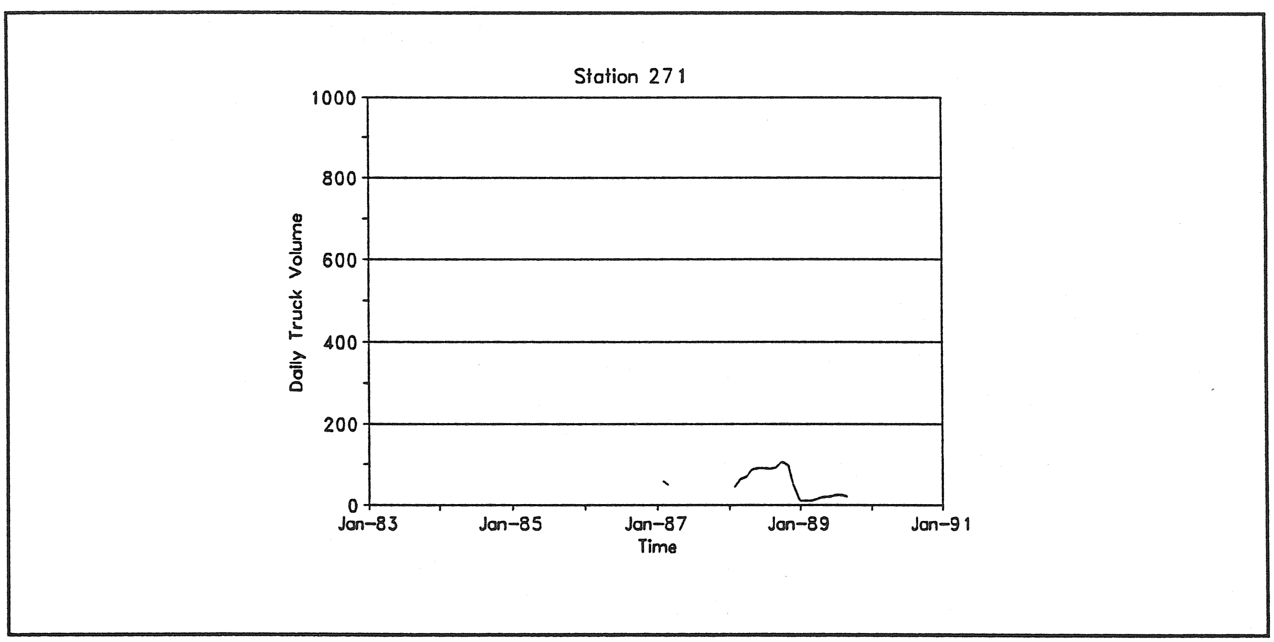

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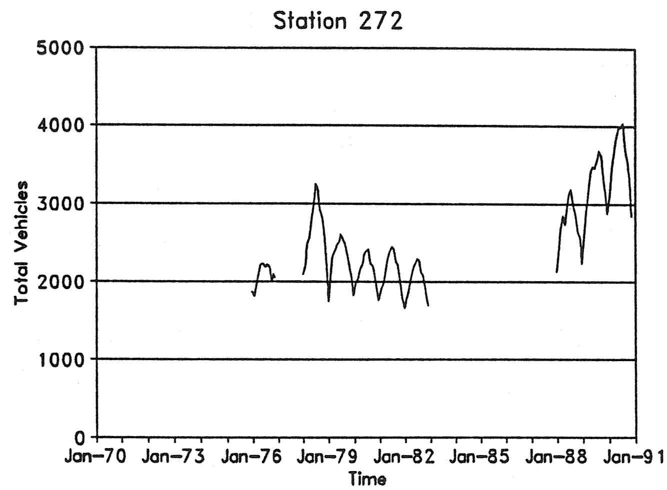

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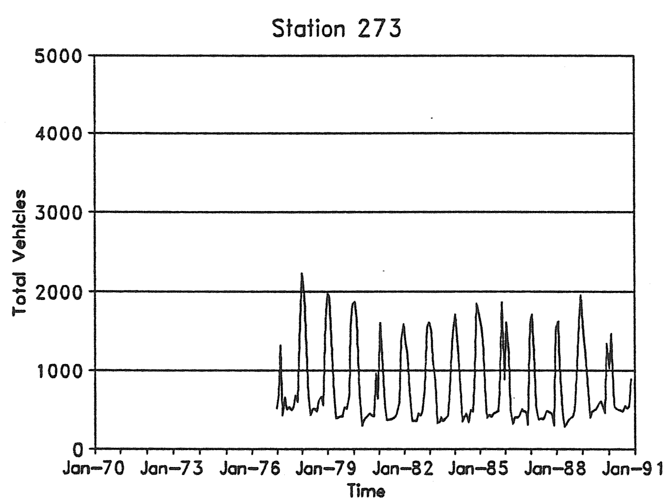
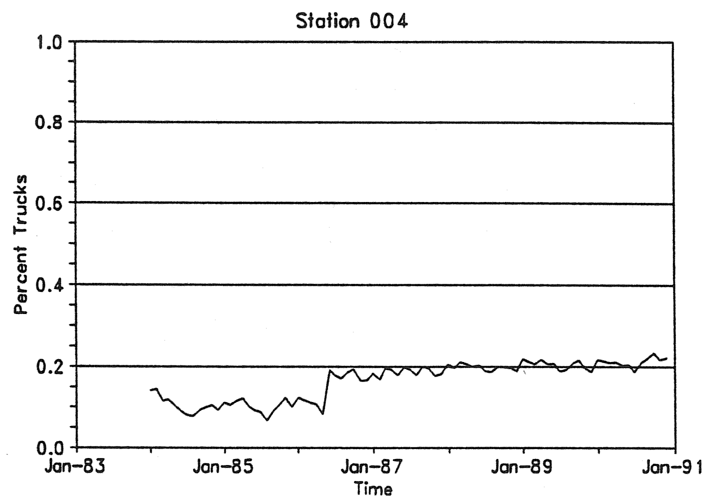


Figure 38

Table 1. ATR Stations for Traffic Composition (Percent Trucks) Analysis

Station	Name	Segment	Milepost	Route	District	County	Category
004	S Pocatello	1330	61.87	I-15	5	Bannock	Rural Interstate
005	N Pocatello	2350	83.77	US-91	5	Bannock	Rural Major Collector
007	Jerome	1010	159.23	I-84	4	Gooding	Rural Interstate
025	Sand Hollow	1010	19.1	I-84	3	Canyon	Rural Interstate
027	St Maries	1600	95.34	SH-3	1	Kootneai	Rural Minor Arterial
030	Cotteral	1010	228.68	I-84	4	Cassia	Rural Interstate
060	Alexander	2040	399.2	US-30	5	Caribou	Rural Principal Arterial
072	Mullan	1660	69.31	I-90	1	Shoshone	Rural Interstate



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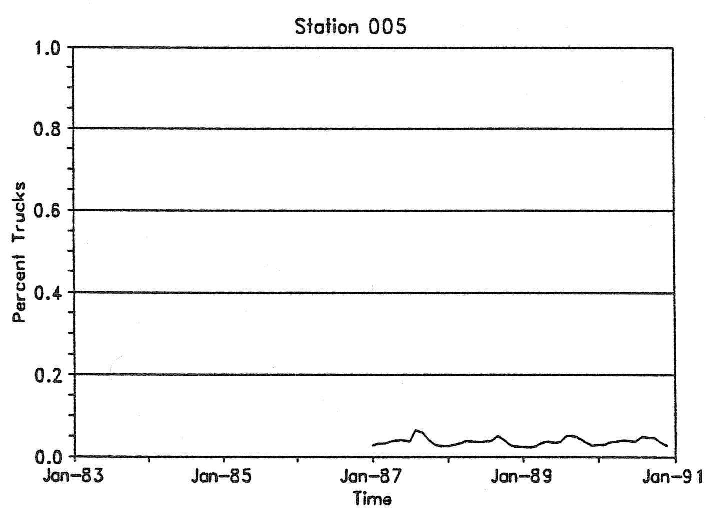

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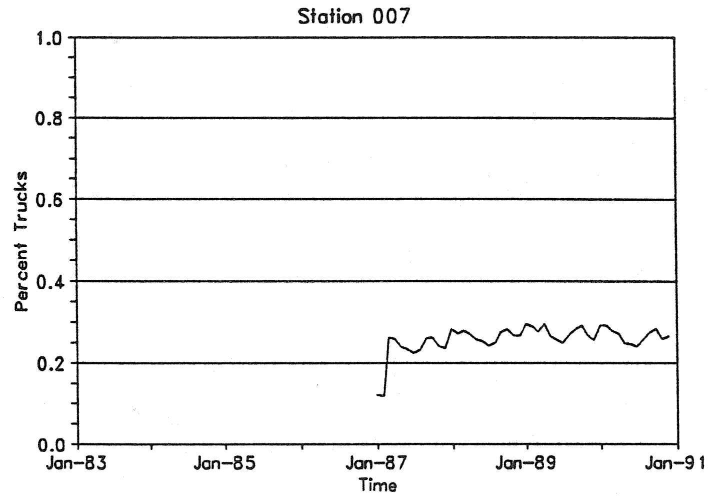

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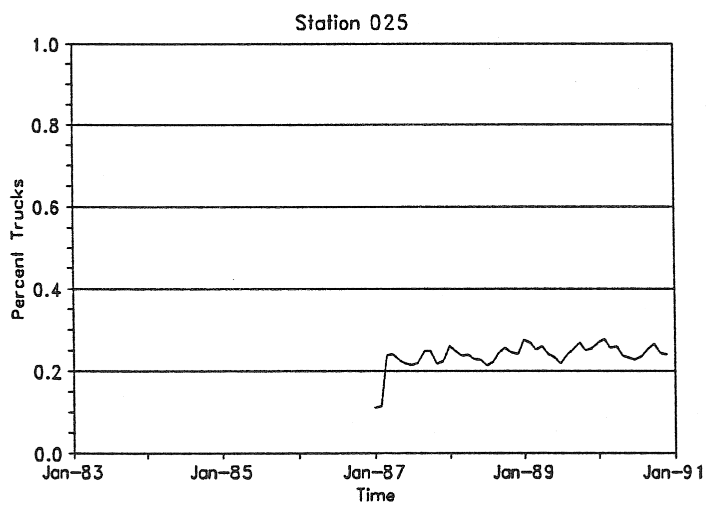

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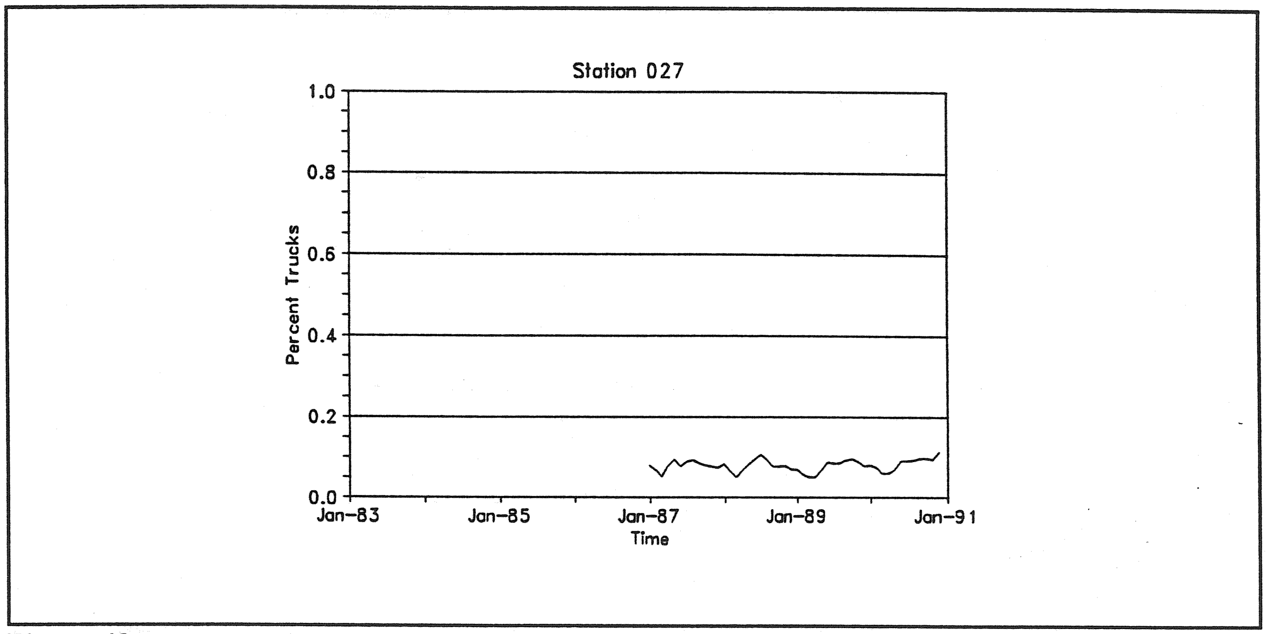

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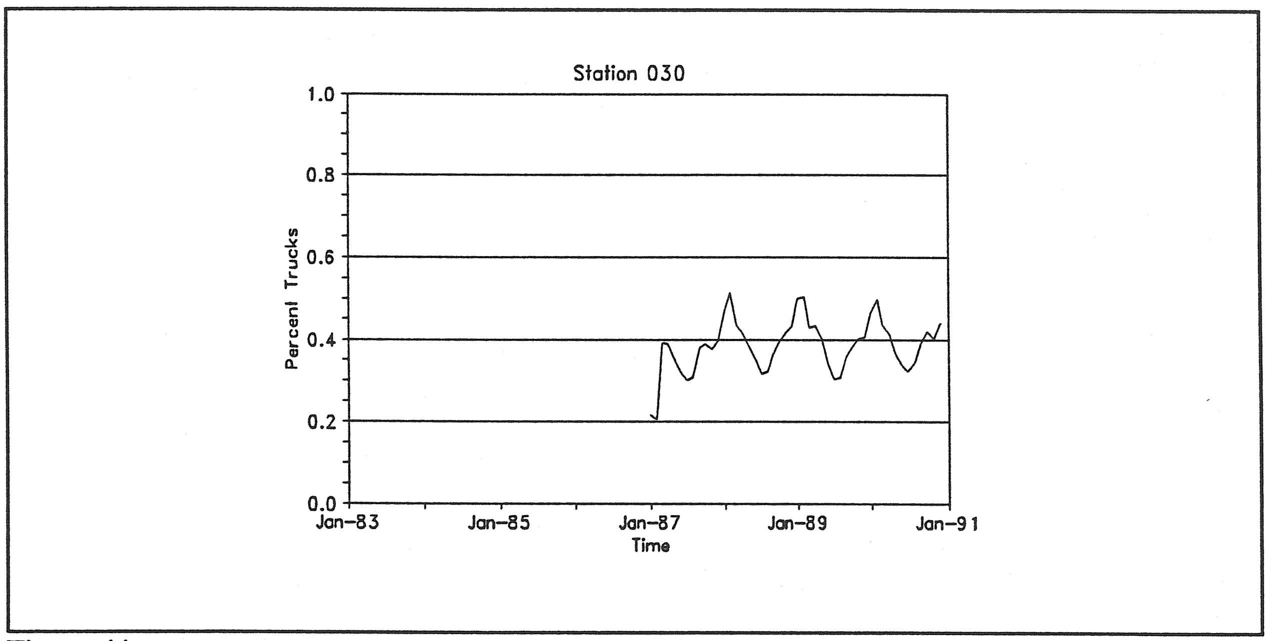

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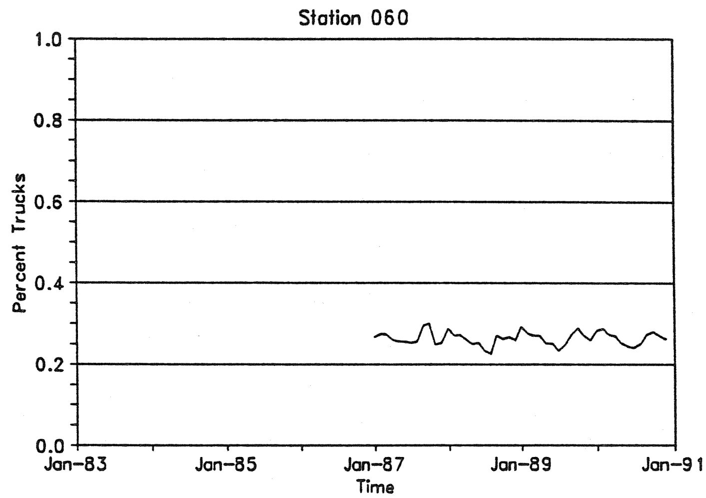

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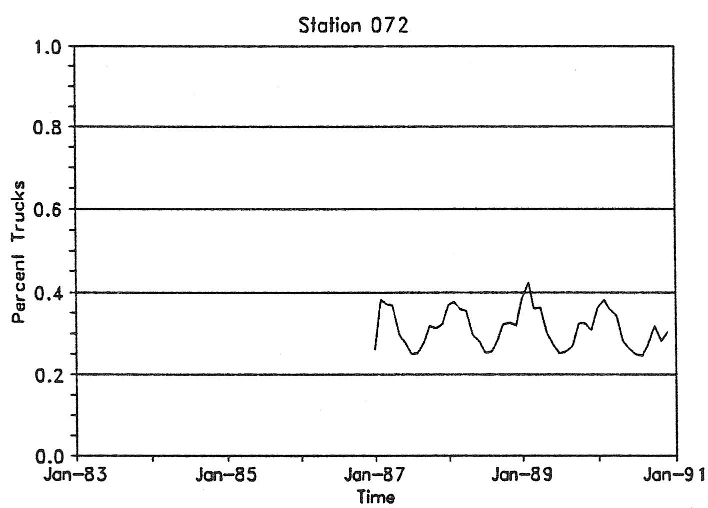

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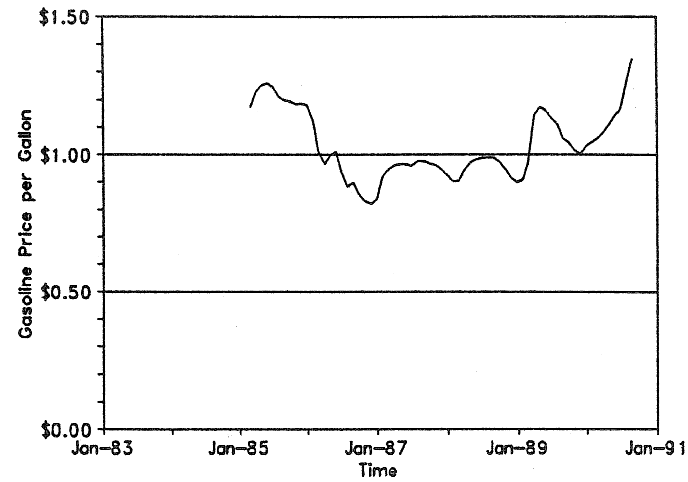

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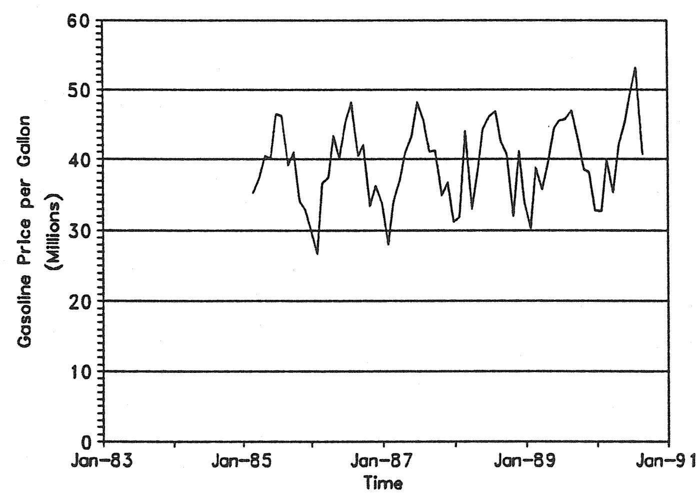

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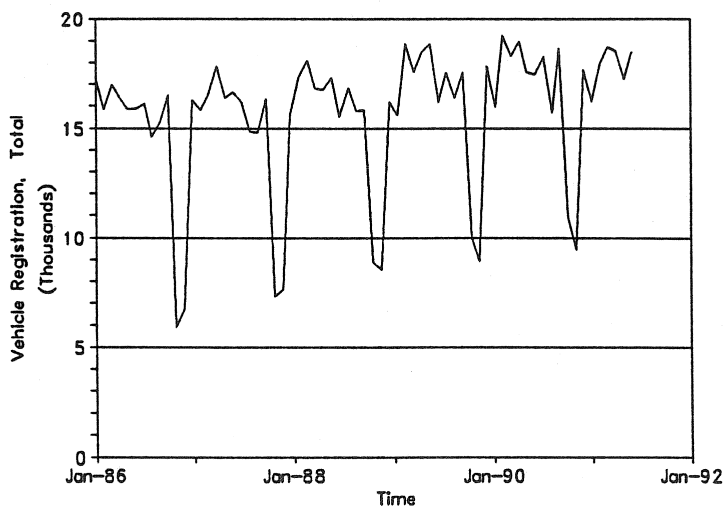

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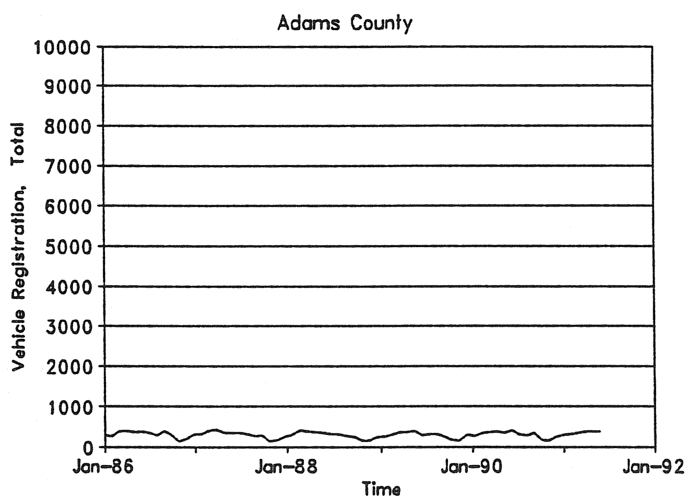

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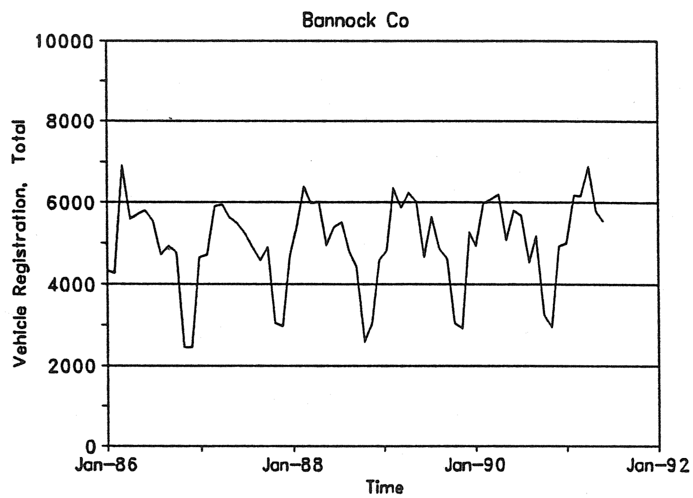

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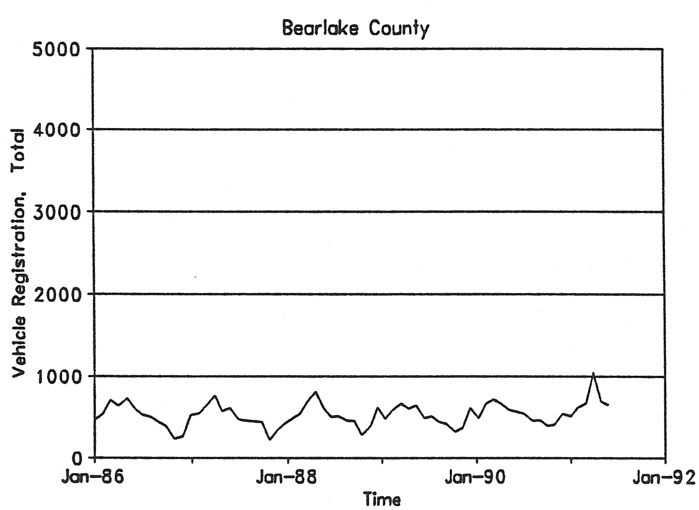

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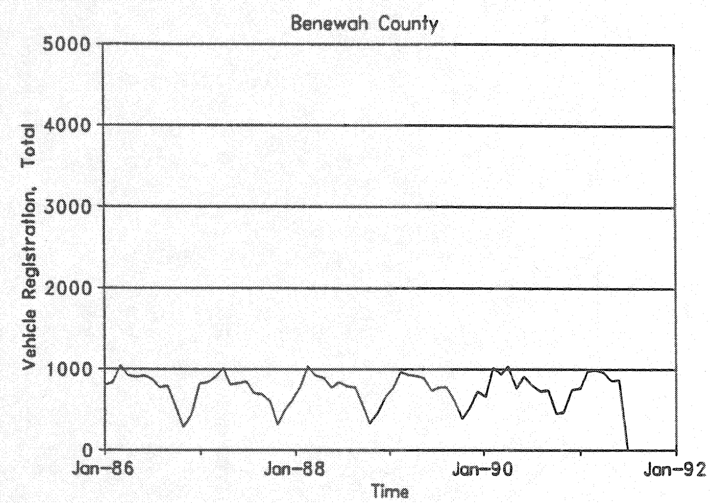

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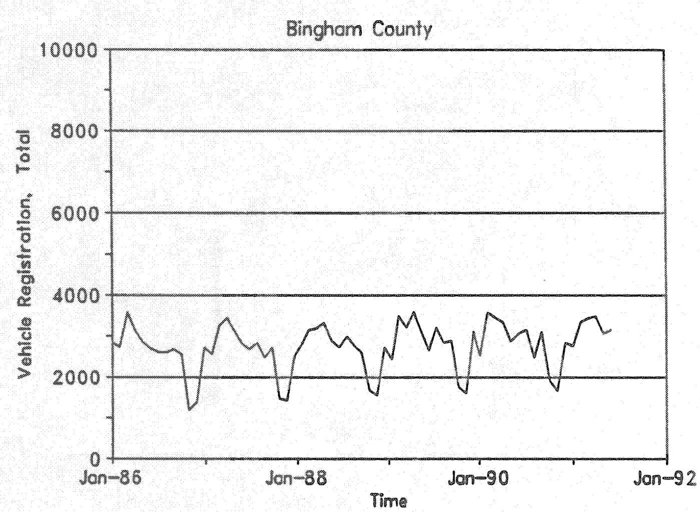

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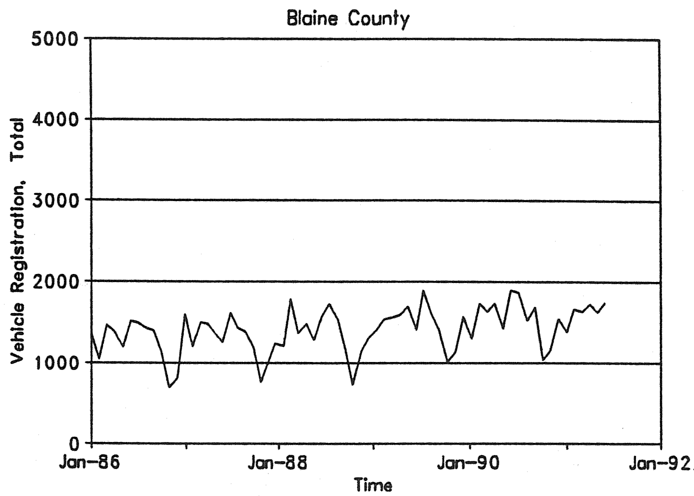

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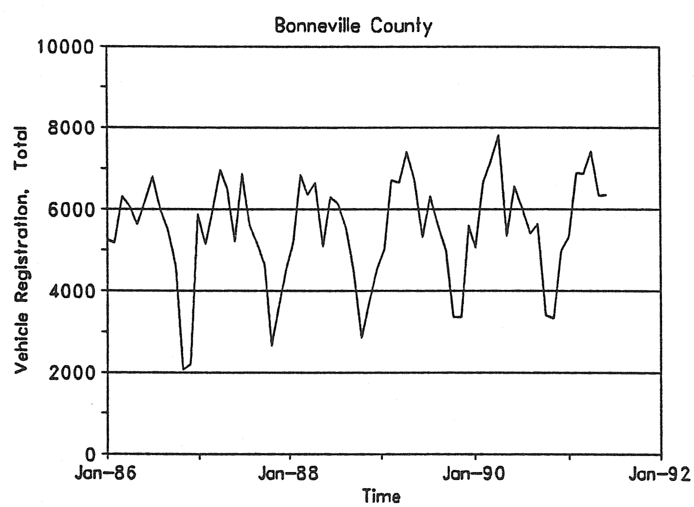

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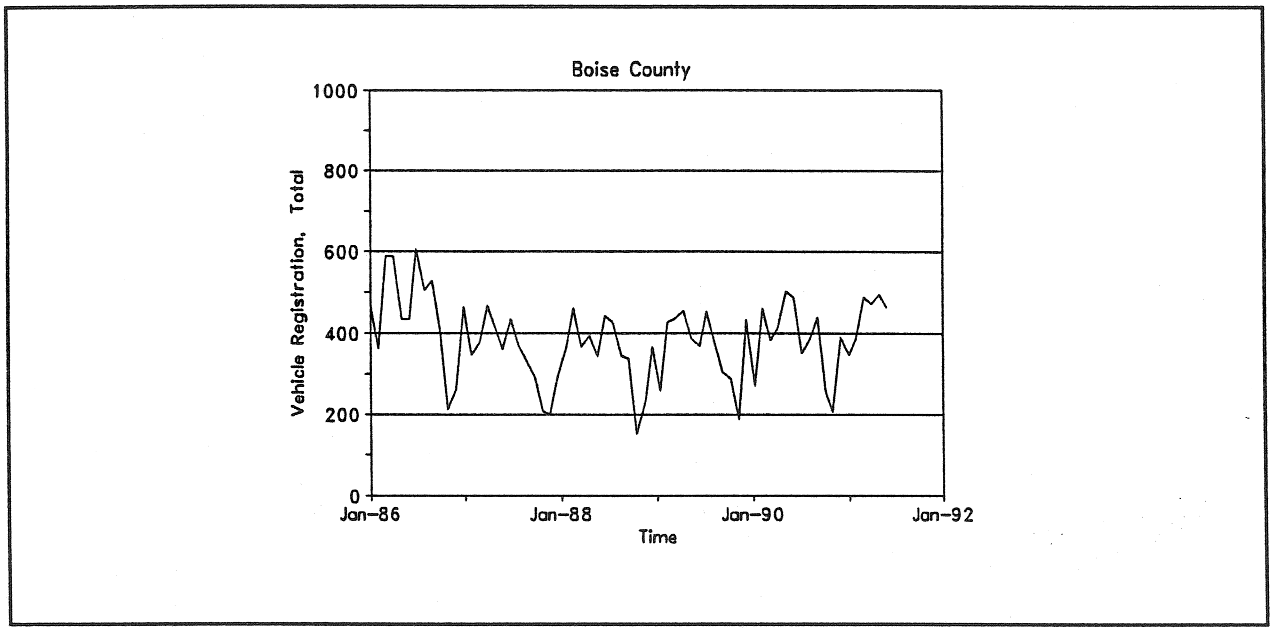

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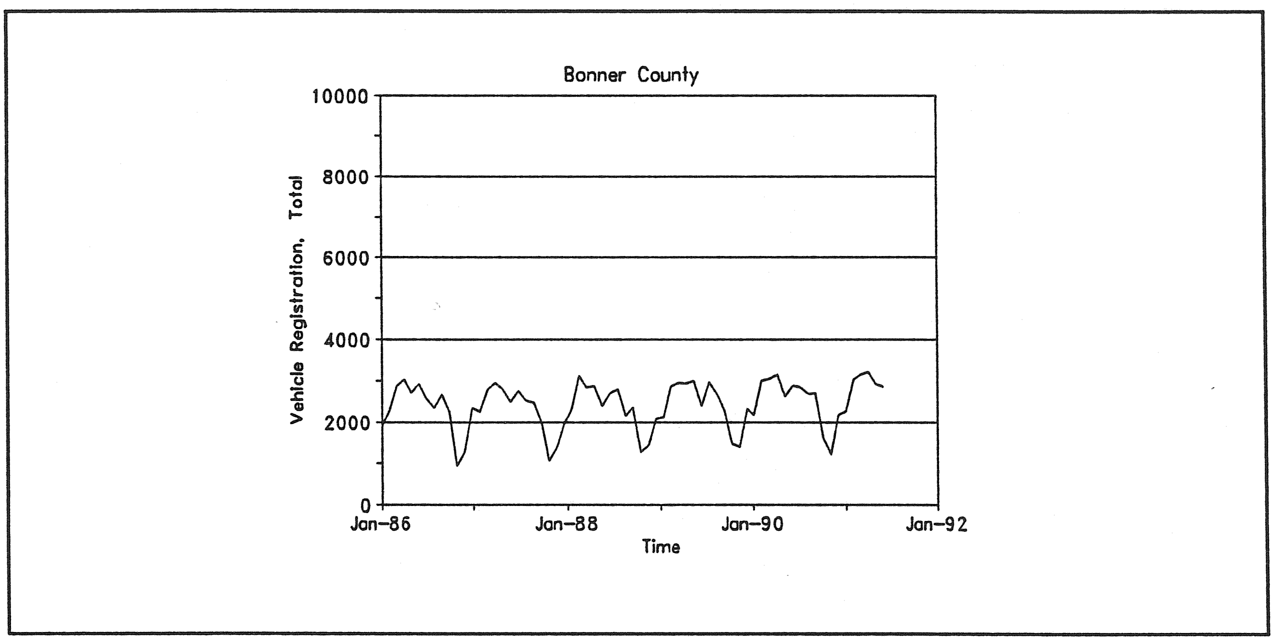

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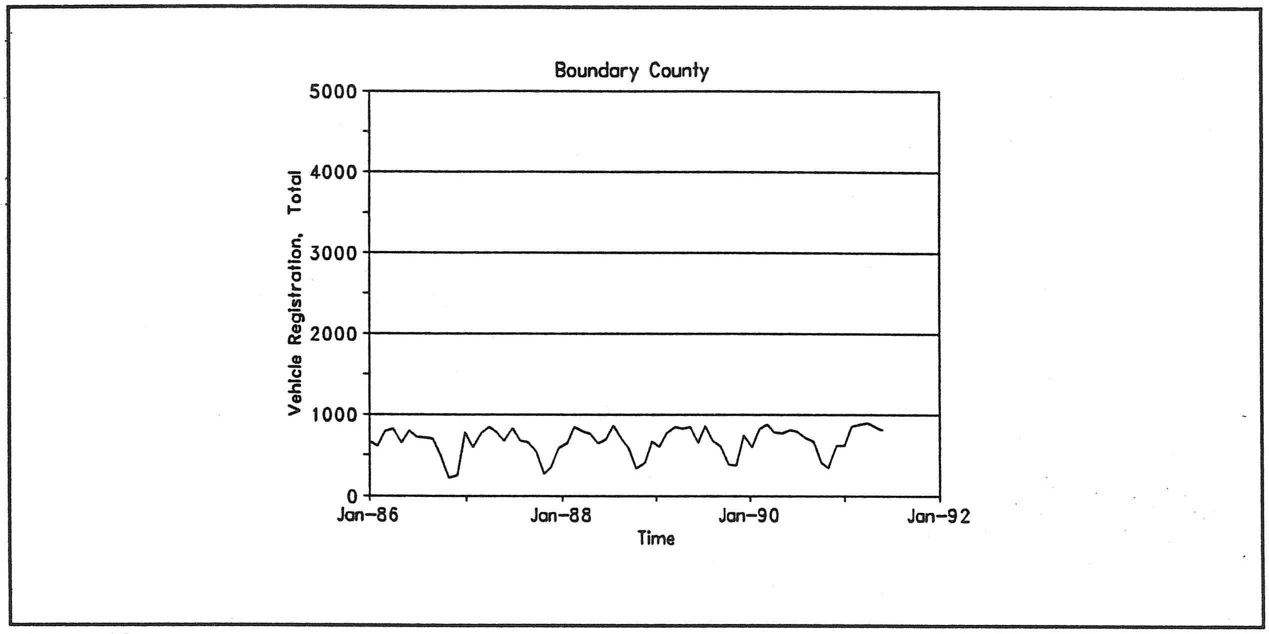

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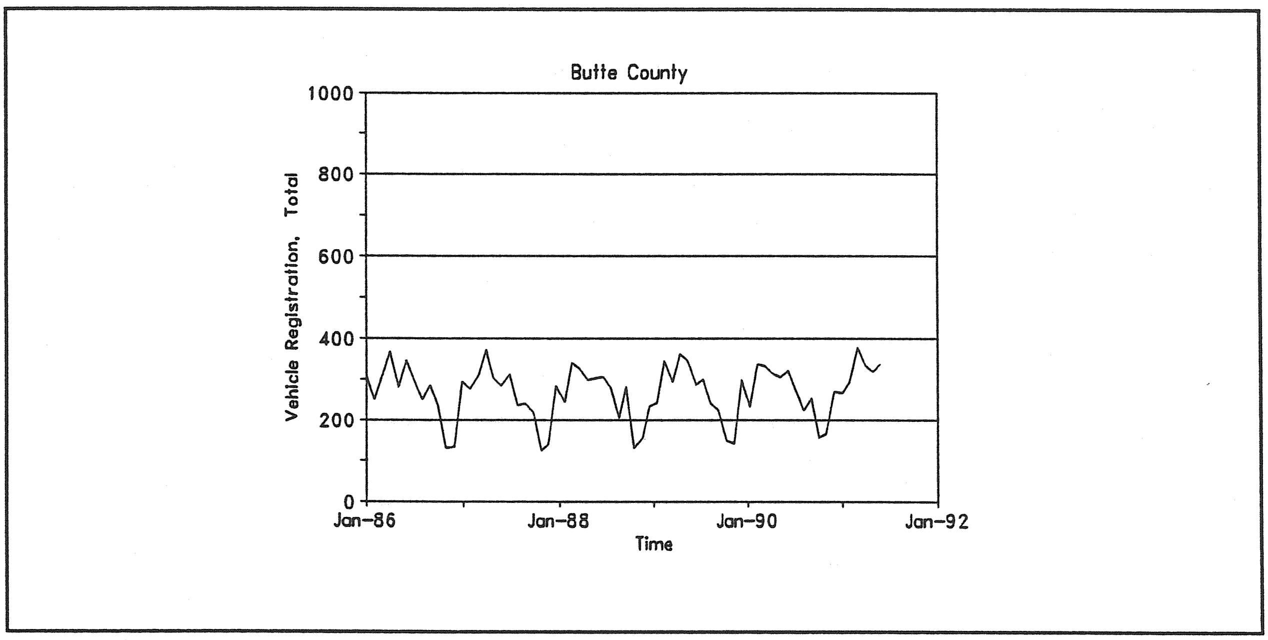

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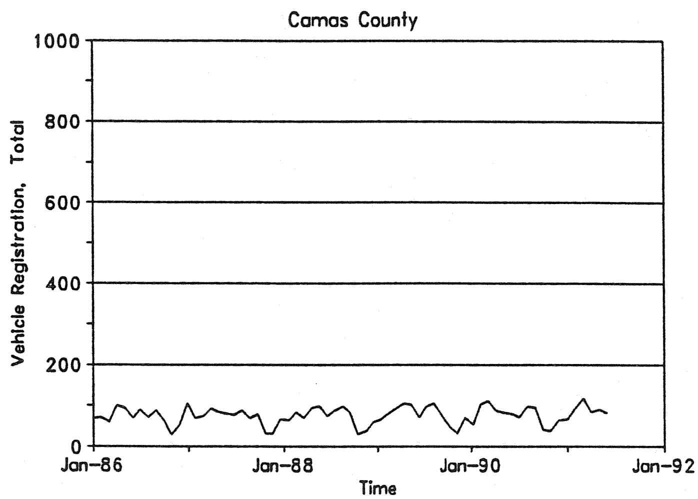

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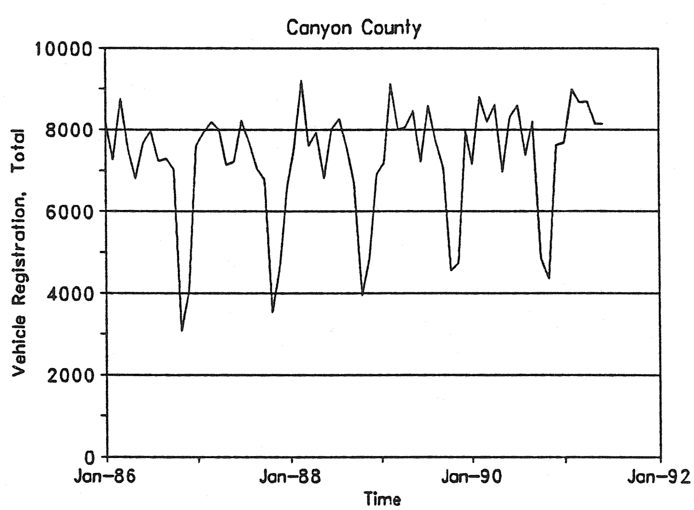

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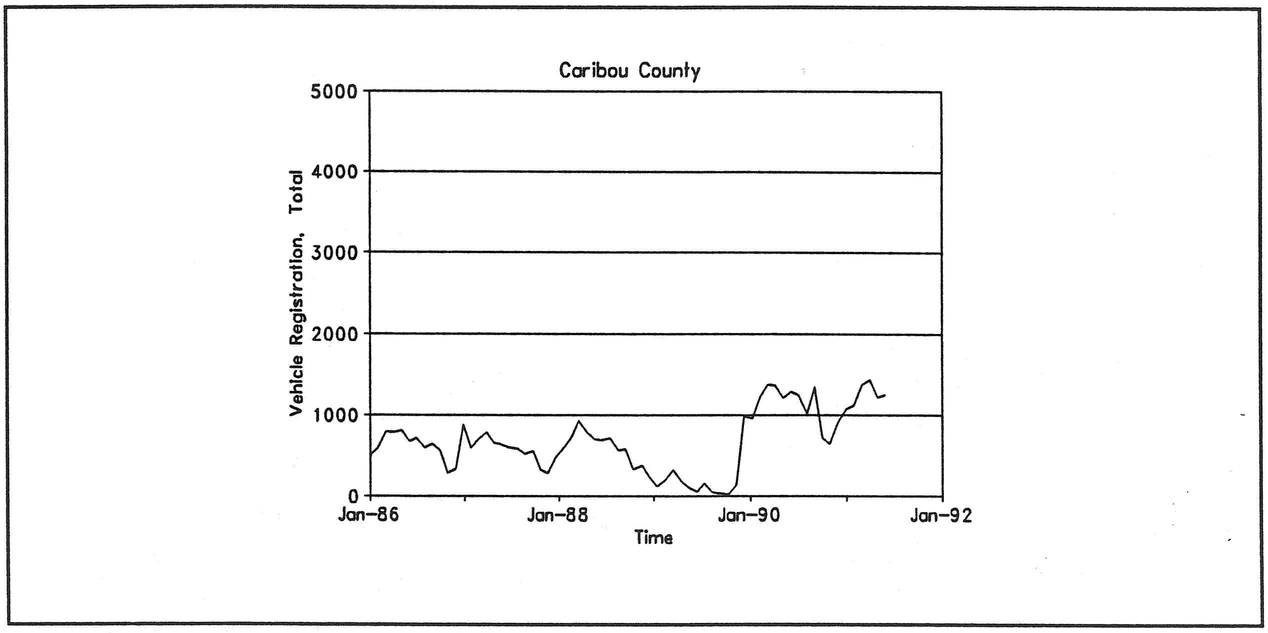

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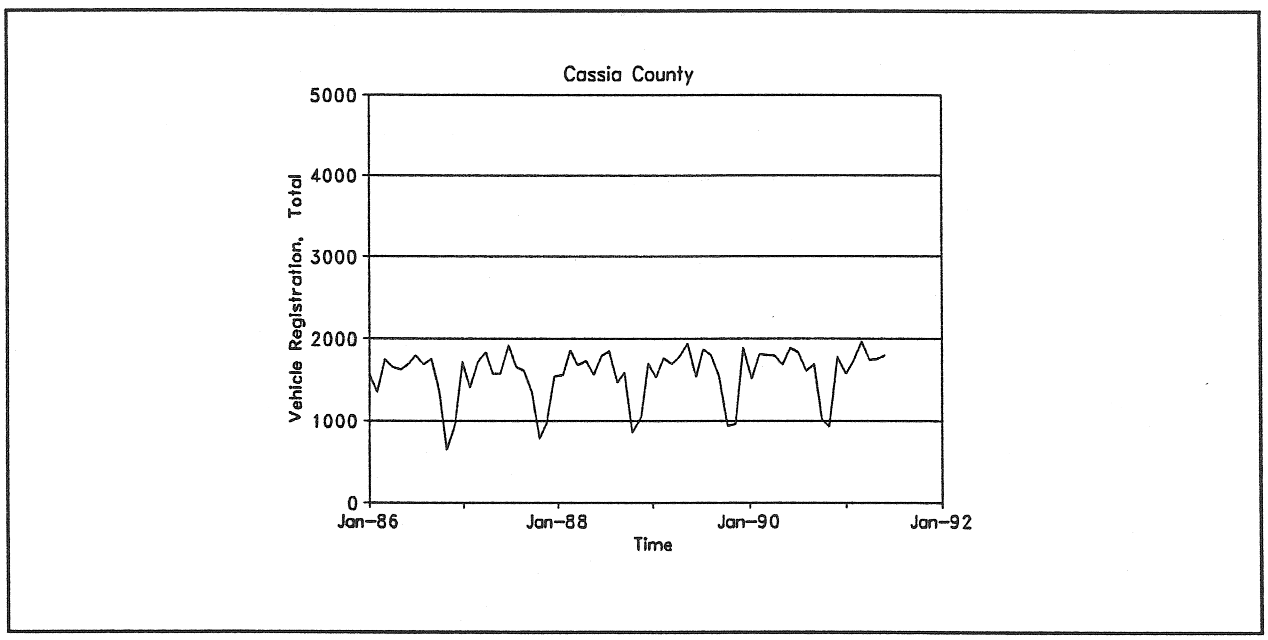

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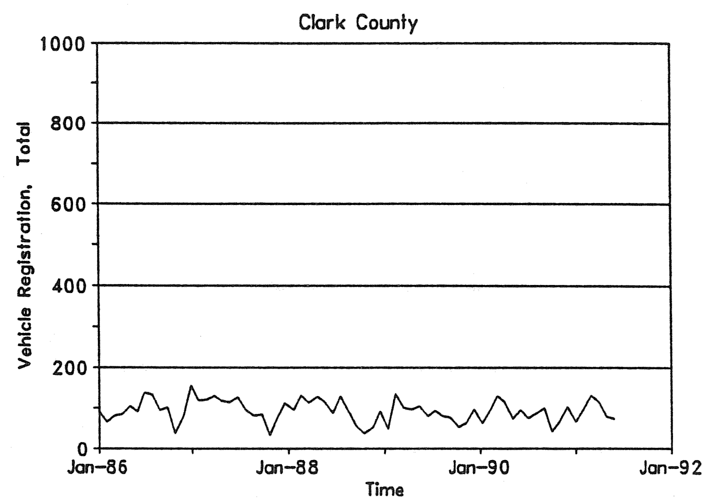

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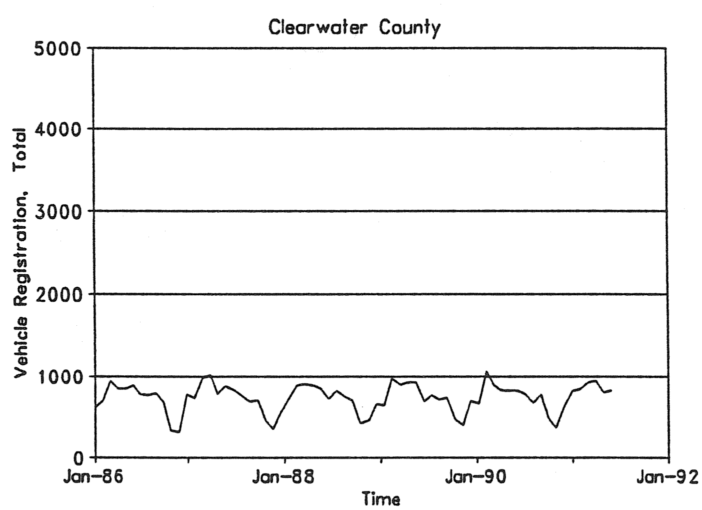

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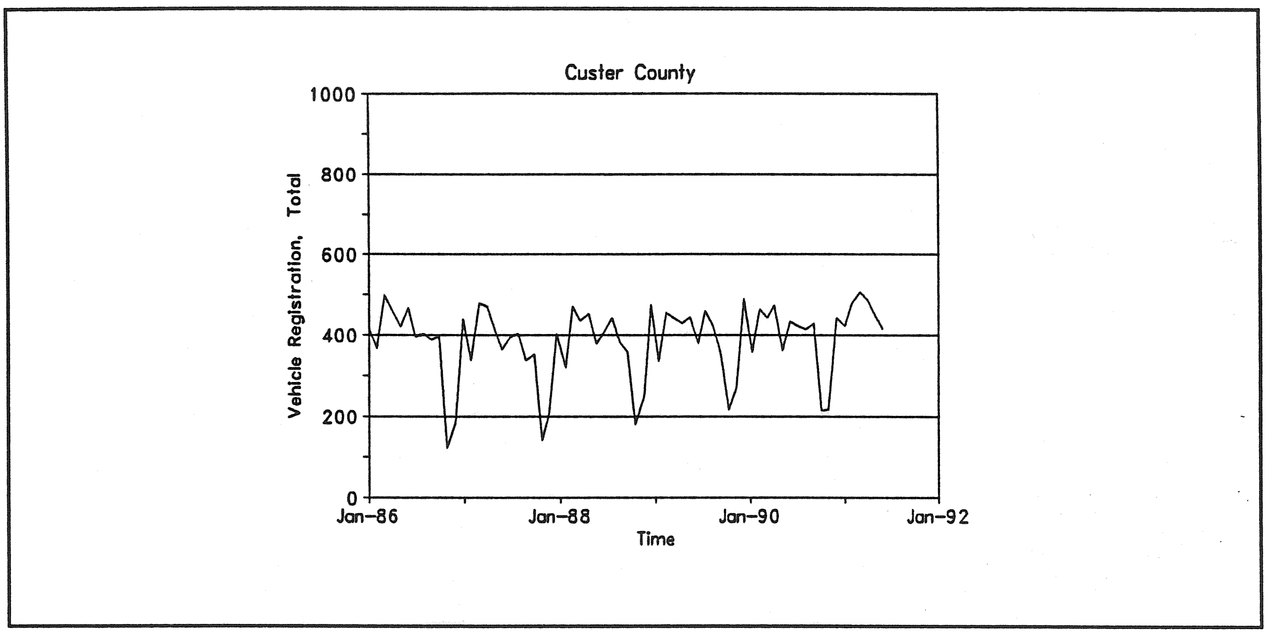

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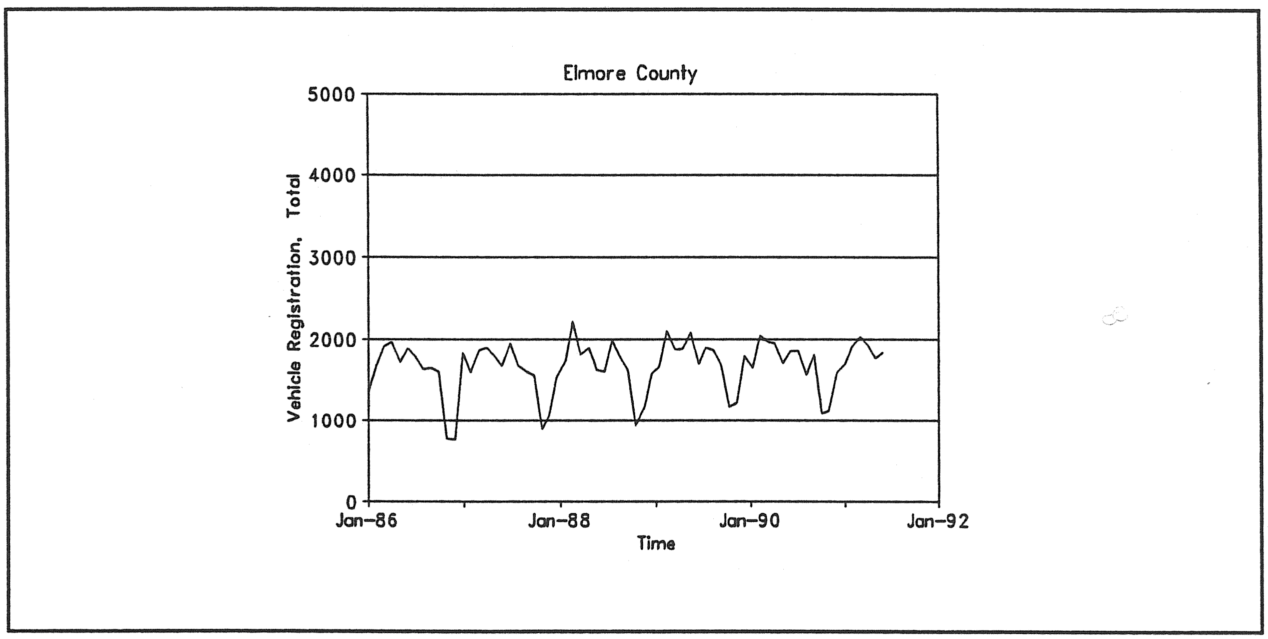

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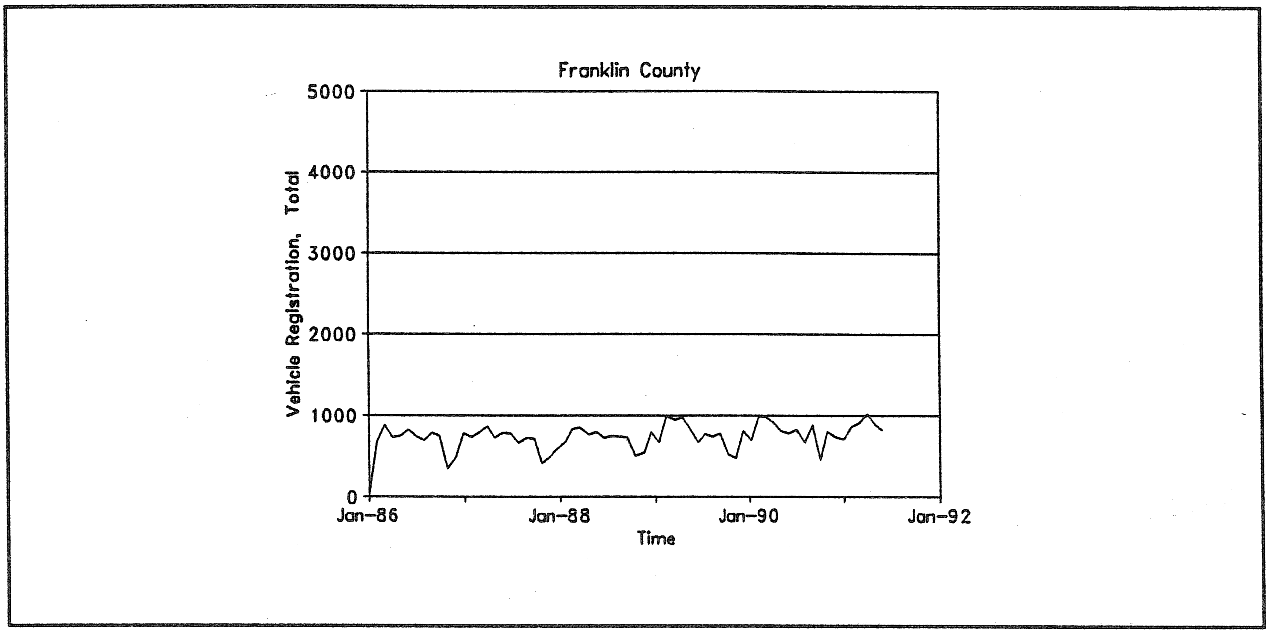

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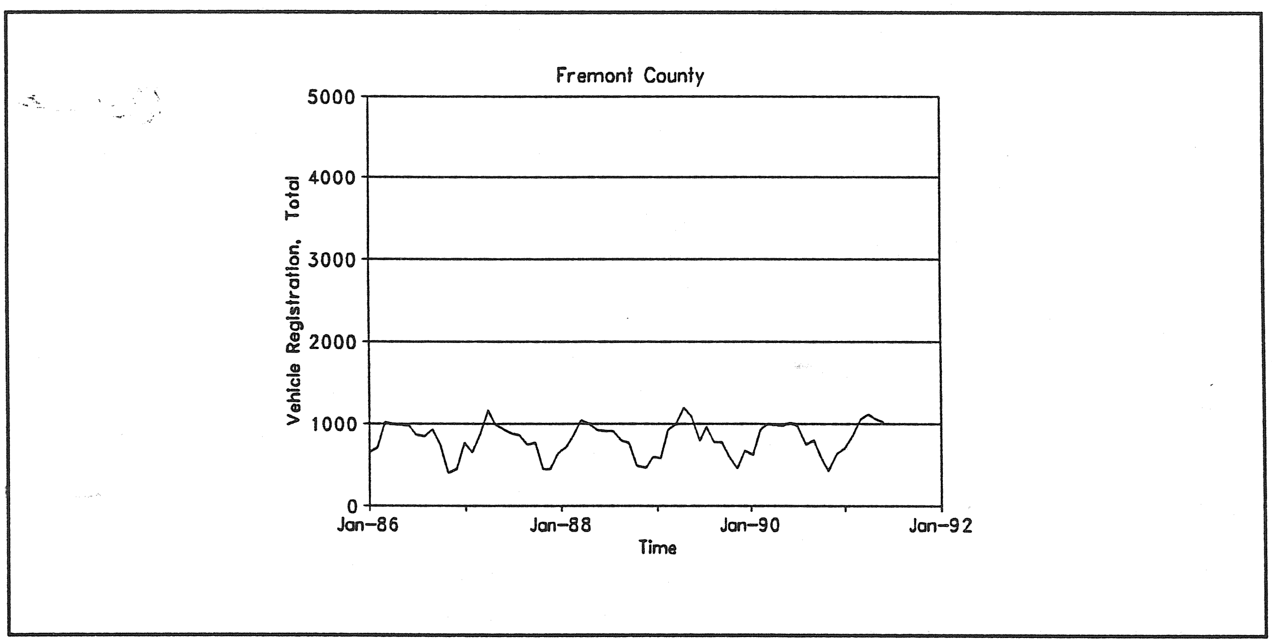

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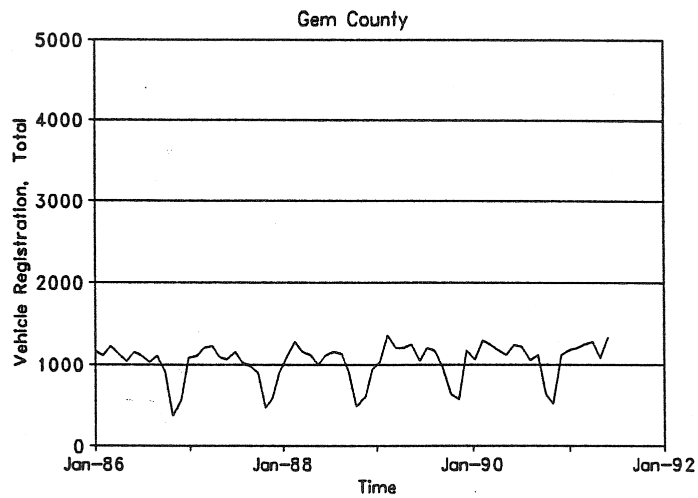

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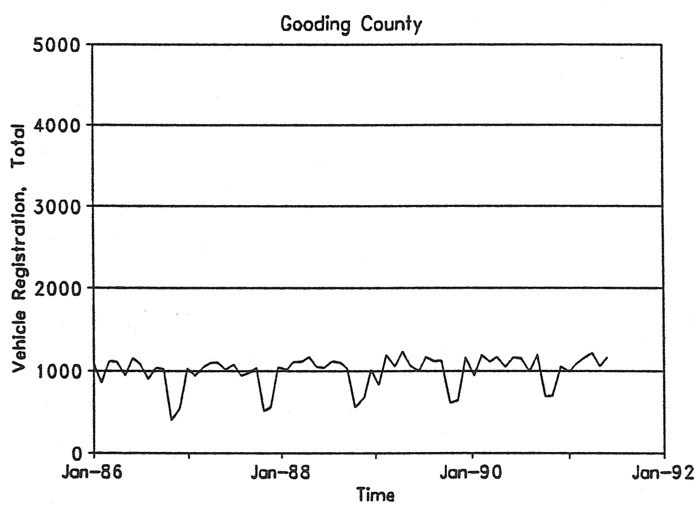

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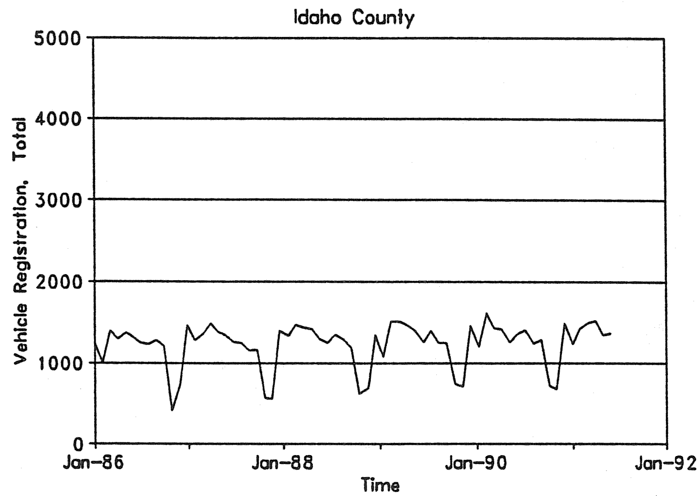

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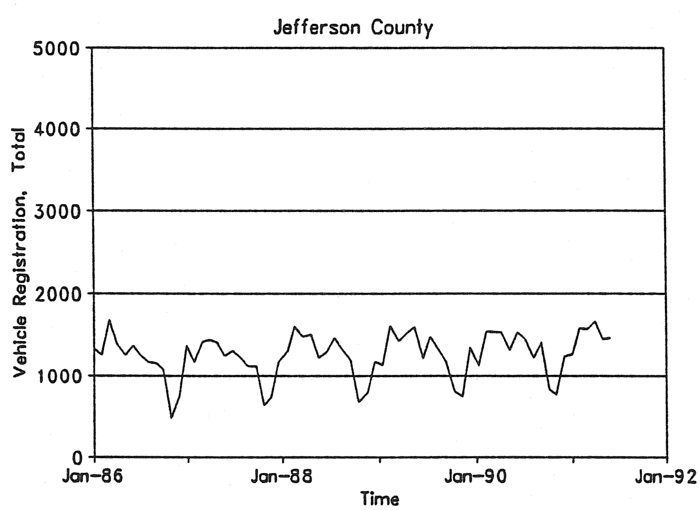

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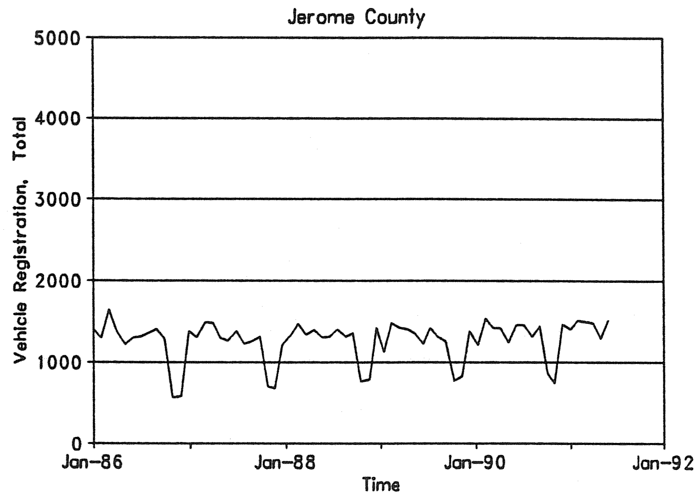

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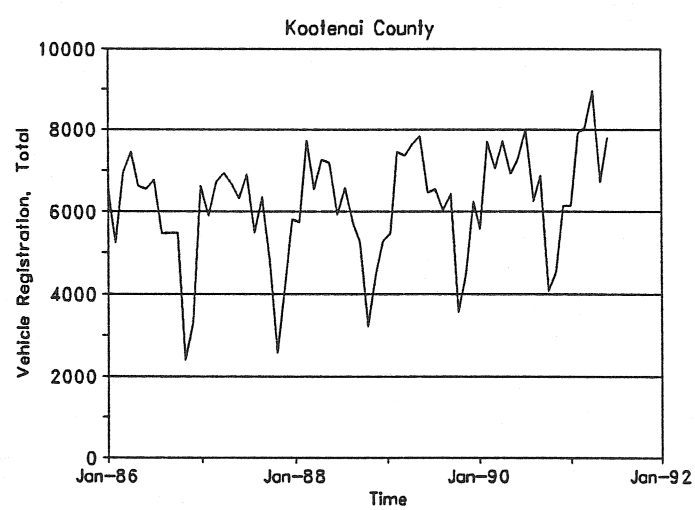

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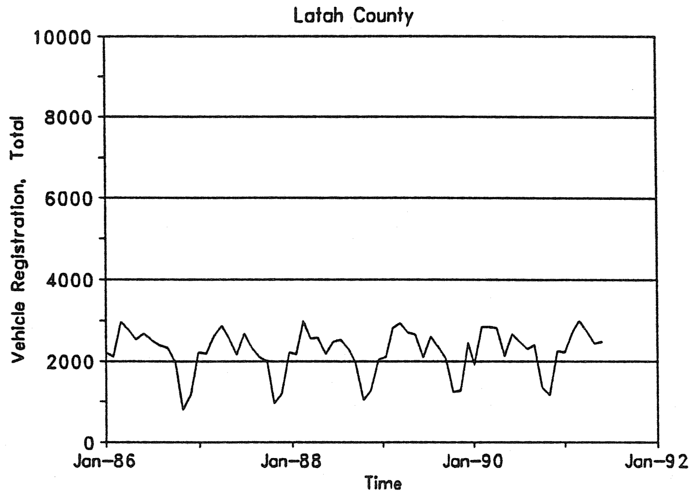

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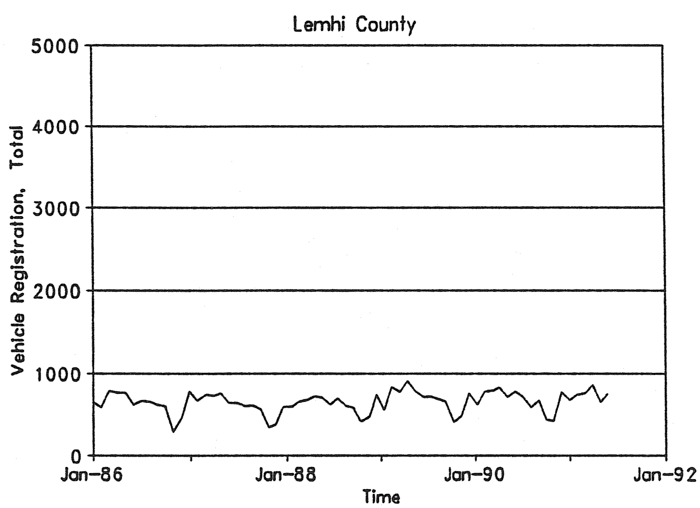

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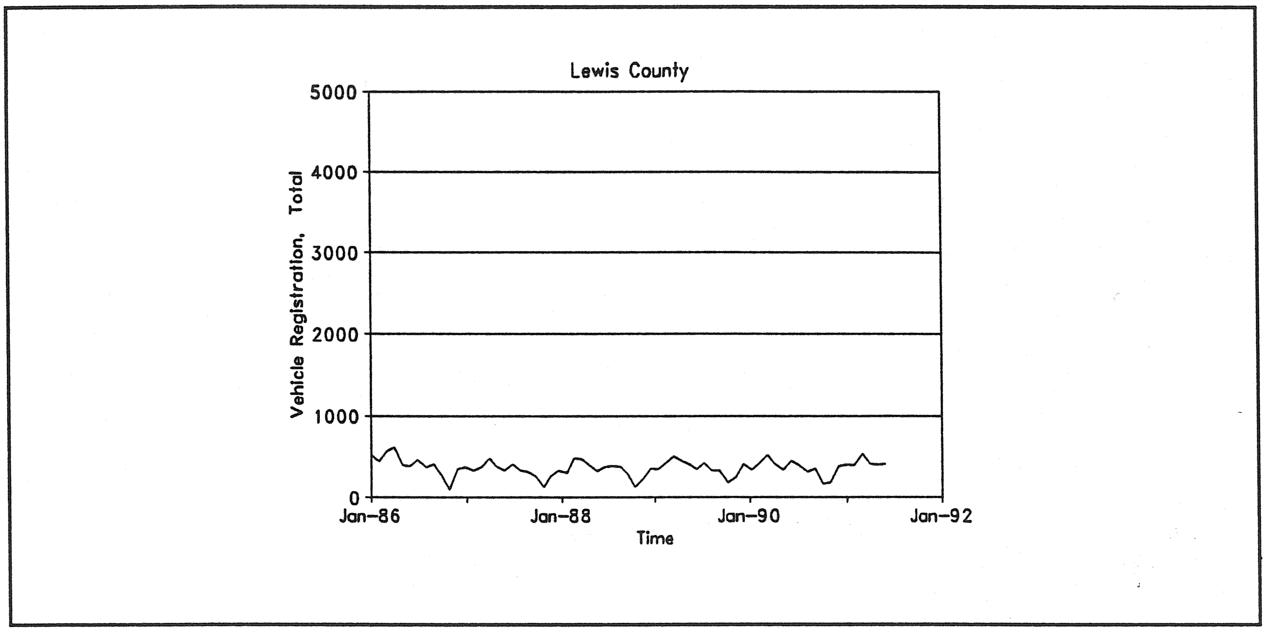

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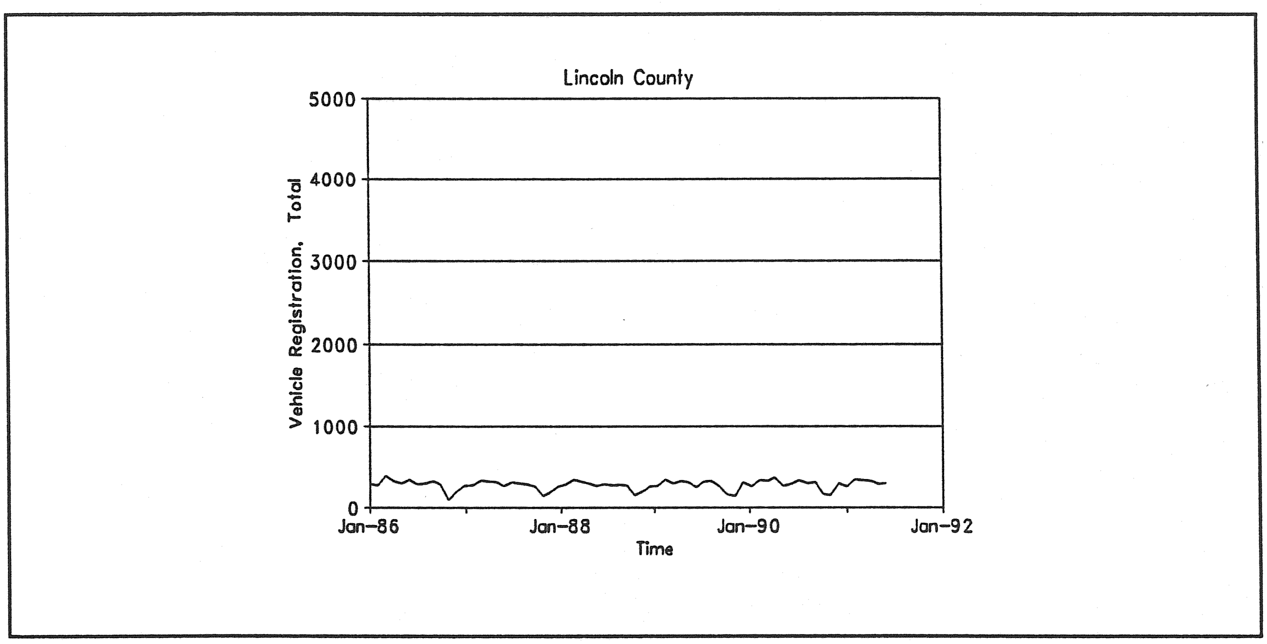

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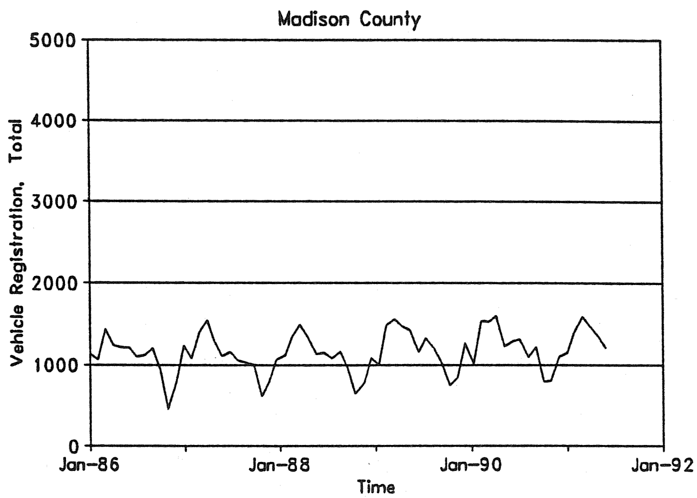

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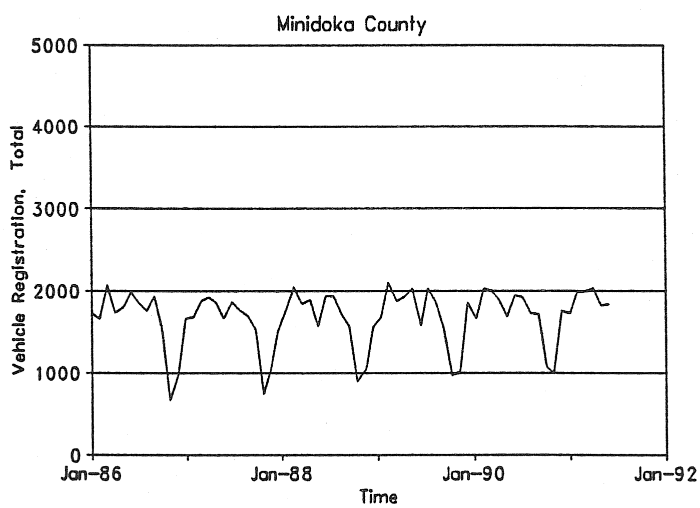

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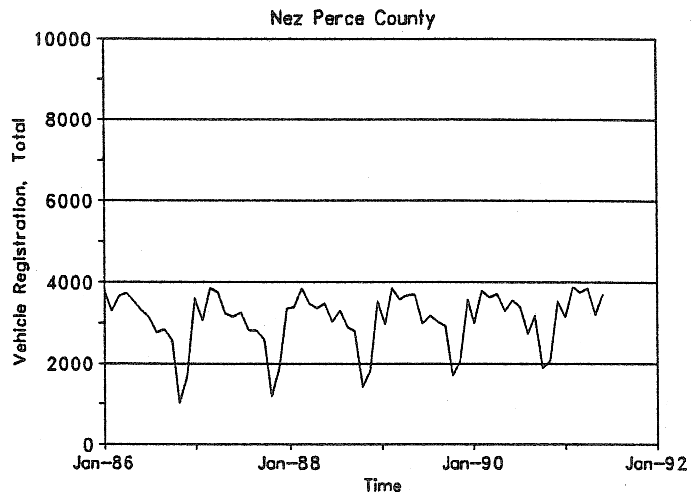

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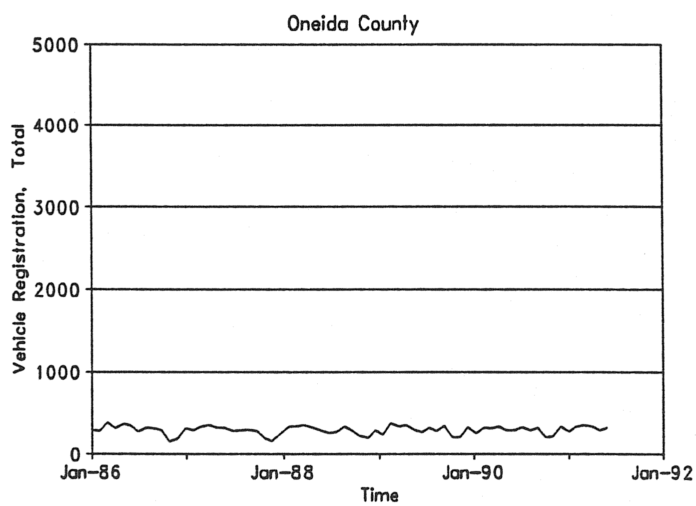

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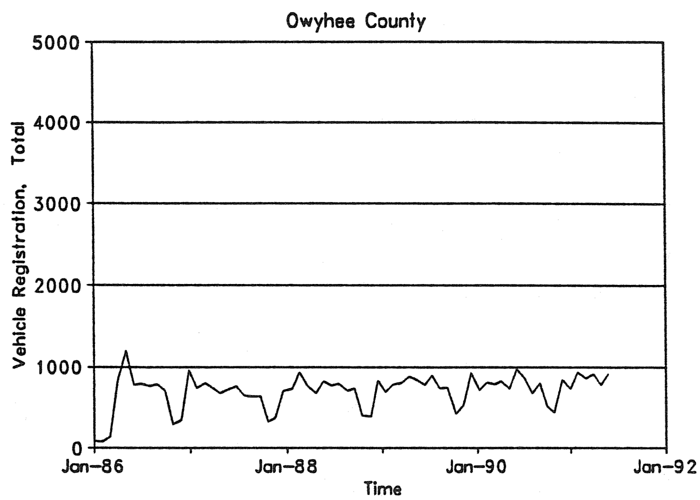

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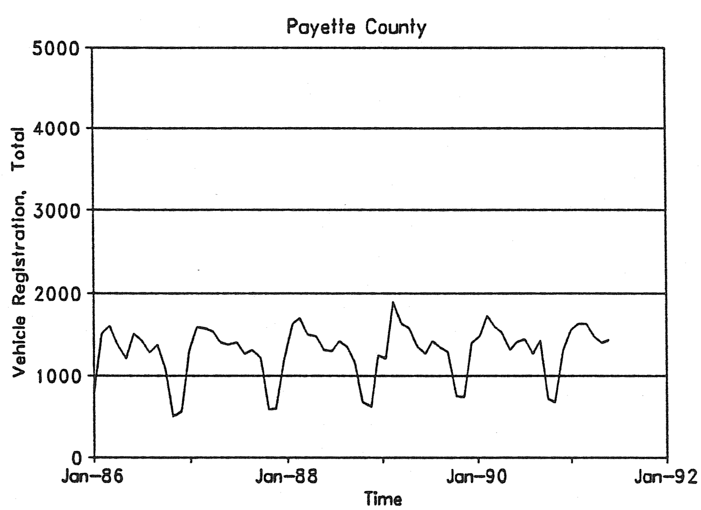

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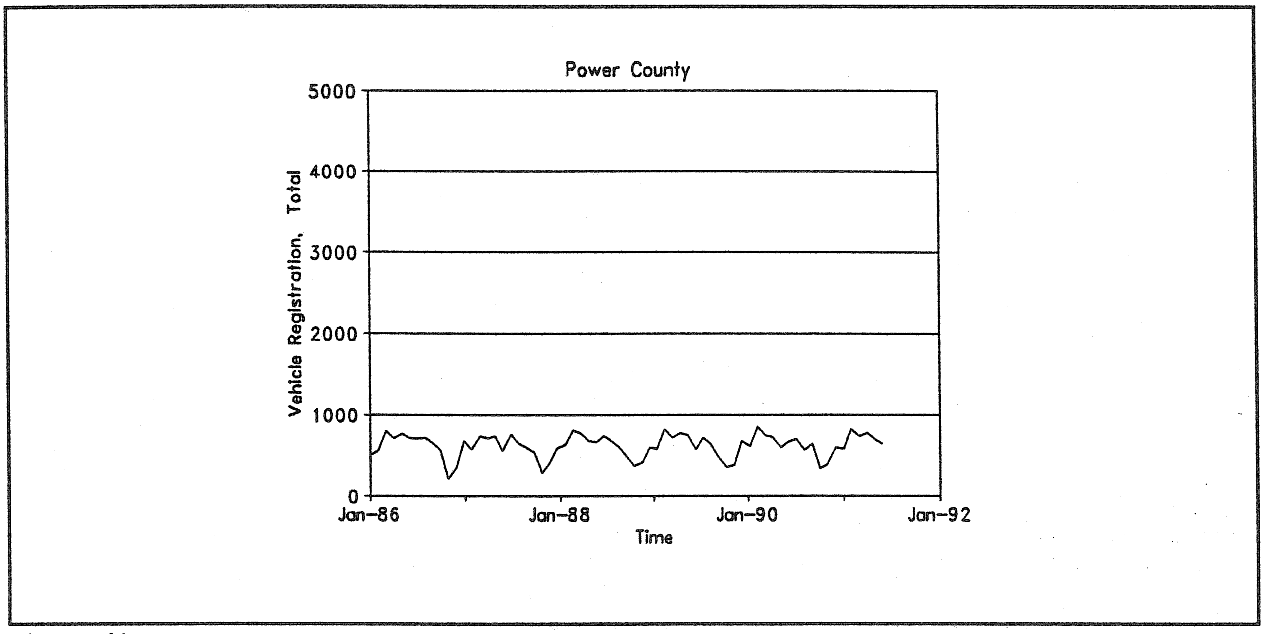

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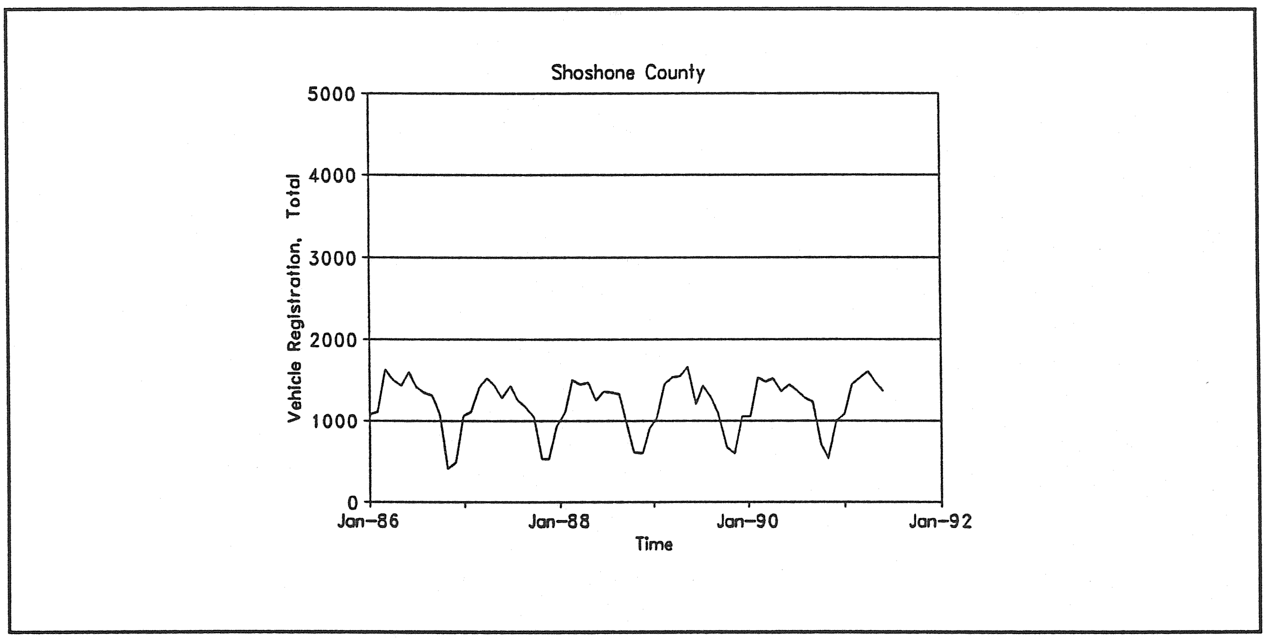

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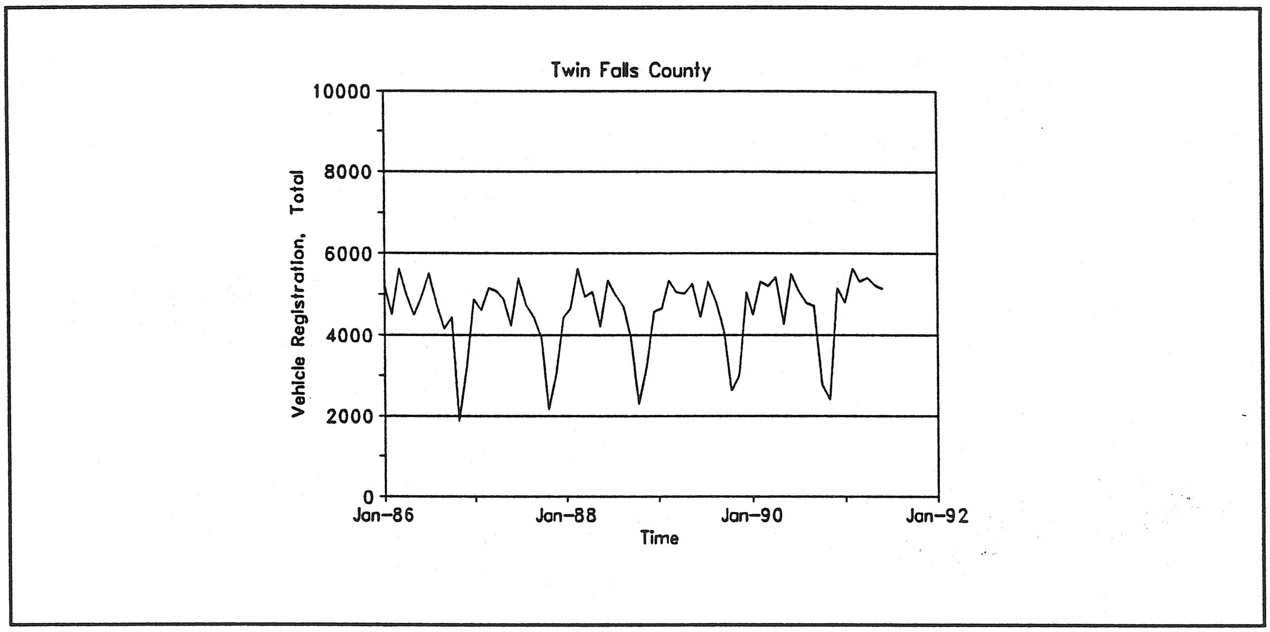

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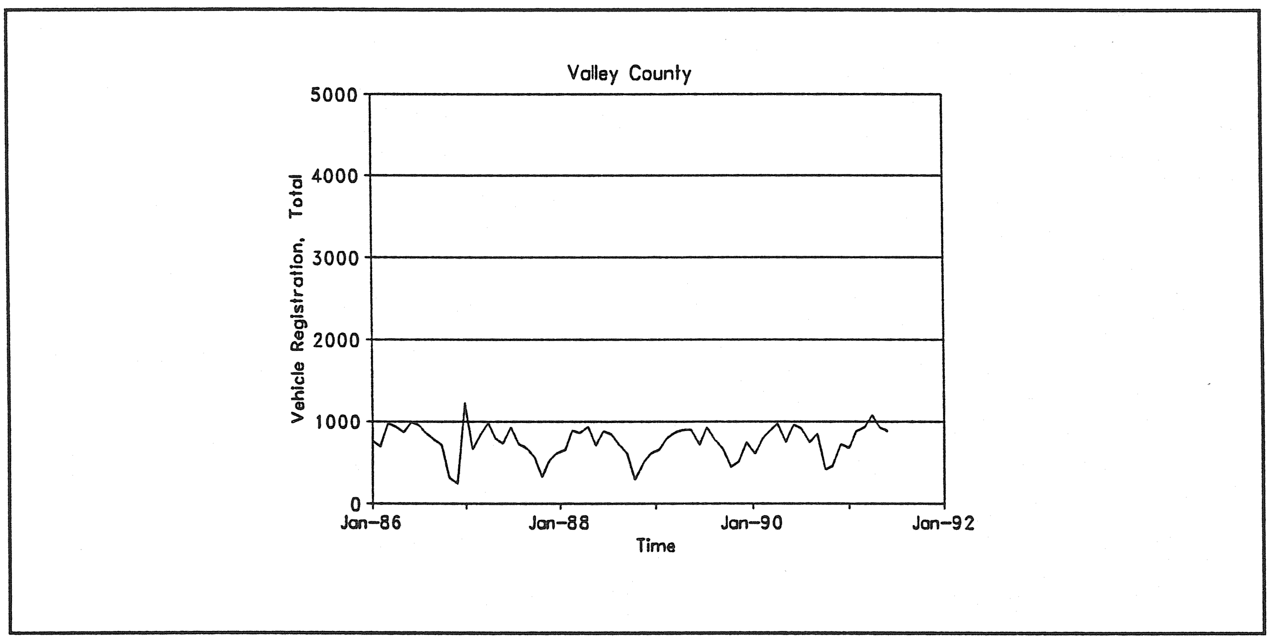

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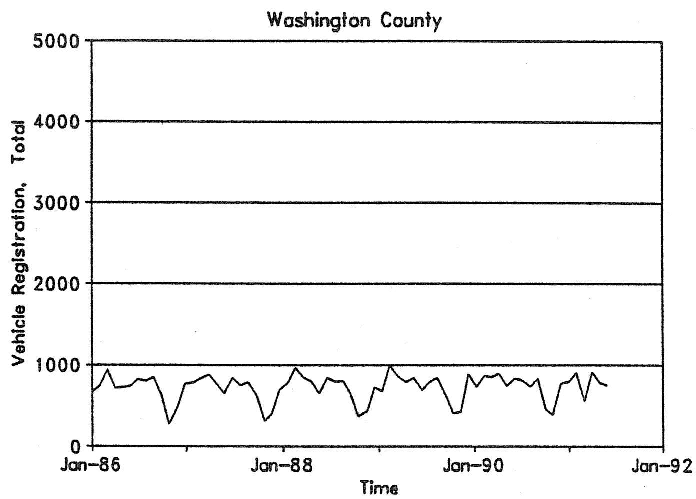
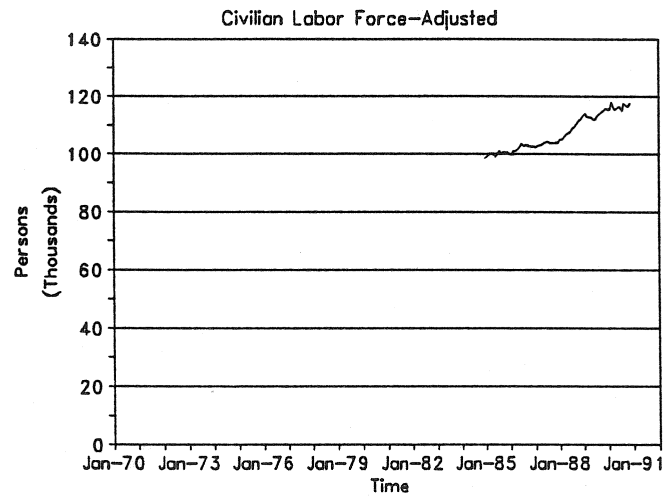

Washington County
Vehicle Registration, Total
5000
4000
3000
2000
1000
0
Jan-86
Jan-88
Jan-90
Jan-92
Time

Figure 45



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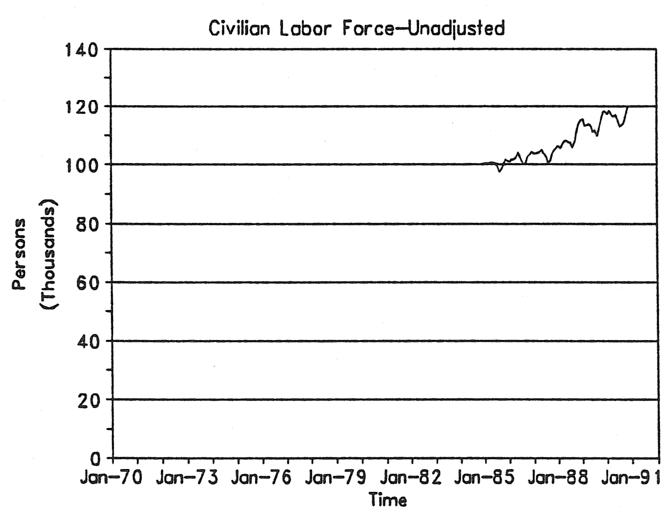

Figure 47

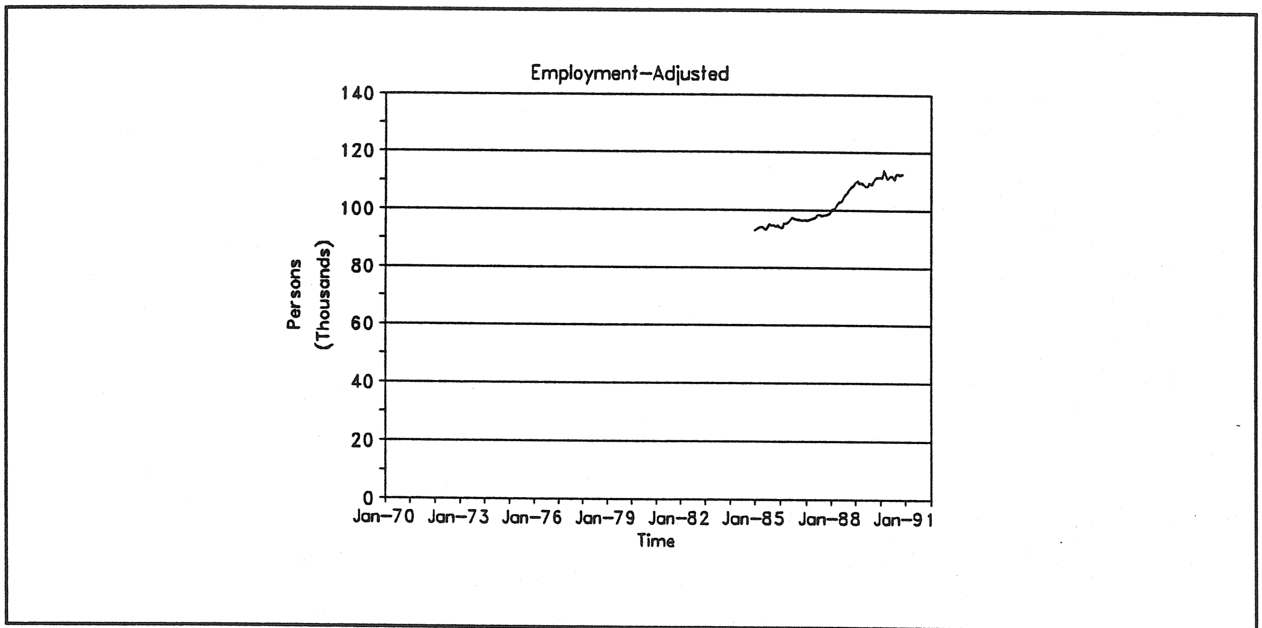

Figure 48

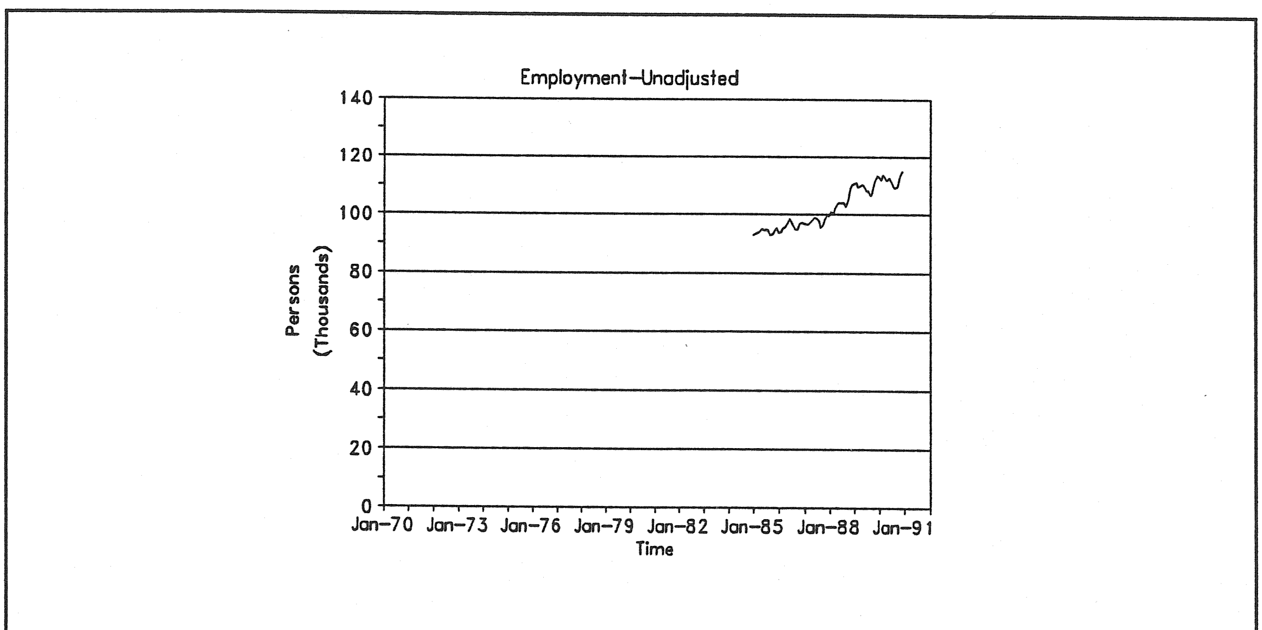

Figure 49